Quantitative Decision Models for Humanitarian Logistics

by

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Abstract

Humanitarian relief and aid organizations all over the world implement efforts aimed at recovering from disasters, reducing poverty and promoting human rights. The purpose of this dissertation is to develop a series of quantitative decision models to help address some of the challenges faced by humanitarian logistics.

The first study discusses the development of a spreadsheet-based multicriteria scheduling model for a small development aid organization in a South American developing country. Development aid organizations plan and execute efforts that are primarily directed towards promoting human welfare. Because these organizations rely heavily on the use of volunteers to carry out their social mission, it is important that they manage their volunteer workforce efficiently. In this study, we demonstrate not only how the proposed model helps to reduce the number of unfilled shifts and to decrease total scheduling costs, but also how it helps to better satisfy the volunteers' scheduling preferences, thus supporting long-term retention and effectiveness of the workforce.

The purpose of the second study is to develop a decision model to assist in the management of humanitarian relief volunteers. One of the challenges faced by humanitarian organizations is that there exist limited decision technologies that fit their needs while it has also been pointed out that those organizations experience coordination difficulties with volunteers willing to help. Even though employee workforce management models have been the topic of extensive research over the past decades, no work has focused on the problem of managing humanitarian relief volunteers. In this study, we discuss a series of principles from the field of volunteer management and develop a multicriteria optimization model to assist in the assignment of both individual volunteers and volunteer groups to tasks. We present illustrative examples and analyze two complementary solution methodologies that incorporate the decision maker's preferences and knowledge and allow him/her to trade-off conflicting objectives.

The third study discusses the development of a decision model for the procurement of goods in humanitarian efforts. Despite the prevalence of procurement expenditures in humanitarian efforts, procurement in humanitarian contexts is a topic that has only been discussed in a qualitative manner in the literature. In our paper, we introduce a two stage decision model with recourse to improve the procurement of goods in humanitarian relief supply chains and present an illustrative example. Conclusions, limitations, and directions for future research are also discussed.

Keywords:

Development Aid, Humanitarian Logistics, Fuzzy Logic, Multicriteria Decision Making, Optimization, Procurement, Scheduling, Spreadsheet Modeling, Stochastic Programming, Volunteer Labor

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Table of Contents

List of Figures

List of Tables

Table **Page**

CHAPTER 1

INTRODUCTION

Chapter 1

Introduction

Introduction

Humanity's top 10 problems over the next 50 years include poverty, disease, education, and population (Smalley 2003). In addition, the impact of natural and man-made disasters cannot be underestimated. Annually, 500 disasters affect some 200 million people and take the lives of around 75 000 people (van Wassenhove 2006). Unfortunately, disasters will continue to cause significant human life and economic losses. The number of natural and man-made disasters is expected to increase five times over the next fifty years (Thomas and Kopczak 2005). Among the reasons that help explain such increase are the effects of population growth and the concurrent stress on the natural environment (Long 1997). At the same time, the annual economic losses caused by disasters have grown significantly: from US$75.5 billion in the 1960's, to US$659.9 billion in the 1990's (Thomas and Kopczak 2005), while current estimates for the economic losses associated with the 2005 Hurricane Katrina alone range between $100 and $150 billion.

As indicated by van Wassenhove (2006), the provision of supplies is the most expensive part of a humanitarian effort and is largely dependent on supply chain management functions such as procurement (the acquisition of goods and/or services) and transportation. Estimates indicate that logistics activities account for 80 percent of relief operations (Trunick 2005), reinforcing the idea that supply chain management is an important factor in humanitarian operations.

However, the field of humanitarian logistics has so far received limited attention by logistics academics and practitioners even though different authors have pointed out that humanitarian supply chain management is one of the most challenging supply chain and logistics domains (Moody 2001; Kovács and Spens 2007; Ratliff 2007). While the social sciences, economics and humanities literatures have developed a significant amount of work on different aspects of relief management, this has not been the case for the decision sciences and supply chain management communities.

The literature in the area of humanitarian logistics contains handbooks with general procedures developed by Non-Governmental Organizations (NGOs) aimed at standardizing operational activities in humanitarian efforts but, as pointed out by Beamon and Kotleba (2006), little is available in terms of quantitative analysis of humanitarian operations and supply chain management. Bryson, Millar et al. (2002), for example, identified a series of potential contributions from the decision sciences community to the field of disaster management. Altay and Green (2006) made the claim that the randomness of the impacts and problems caused by disasters demand dynamic, real-time, effective and efficient solutions, thus making the topic very suitable for quantitative modeling research.

The present work is focused on humanitarian supply chain management and employs different quantitative modeling techniques to address some of the challenges faced by humanitarian logistics. More specifically, two multiobjective scheduling models to support the assignment of volunteer work-force in humanitarian operations are developed. One model is focused on humanitarian aid for long term development, while the second model is focused on humanitarian relief efforts. In addition, we also develop a multistage stochastic model to improve the procurement of goods and services in humanitarian operations.

Challenges of Humanitarian Supply Chain Management

There are a number of specific challenges faced by the field of humanitarian logistics.

First of all, humanitarian supply chains must usually operate in highly uncertain environments. Knowledge about the demand for humanitarian relief (in terms of the magnitude and type of materials and services needed) is fairly unpredictable. The same characteristic applies to the infrastructure and resources available. For example, the available infrastructure may be significantly damaged or disrupted, while the location of relief facilities may change not only from one disaster to the next but also during a single disaster.

With respect to the procurement process, procedures are difficult to enforce as integrity is lacking. Tracking and tracing of shipments is typically done manually using spreadsheets and, furthermore, in most cases there are no central databases of history on prices paid, transit times, or quantities purchased and received (Thomas 2003).

In addition, humanitarian organizations rely heavily on the use of volunteers to implement their humanitarian efforts. However, Bussell and Forbes (2002) found that even though the amount of work required in the volunteer sector is growing, the number of available volunteers is not increasing at a comparable rate. Therefore, it is important for humanitarian organizations to manage efficiently the available volunteer workforce in order to successfully recruit and retain their volunteer bases.

The need of humanitarian relief organizations to avoid waste and to improve the efficiency and effectiveness of their logistics systems is also fostered by requirements from donors. As explained by Lindenberg (2001), not only are resources becoming tighter in humanitarian organizations, but also these organizations are facing increased pressure for greater accountability and better program quality. Thomas (2003) pointed out that usage of funds is not tracked to the extent that donors usually request. Moreover, the author found that data is usually written out onto multiple forms and keyed into multiple spreadsheets and, as a result, budget control is inadequate and funds may be misspent.

Long (1997) argued that information systems are the most important factor in determining the success of a relief logistical efforts and emphasized the uniqueness of each relief operation. Ratliff (2007) also made the claim that there is a very limited number of information and decision technologies that clearly fit the needs of humanitarian relief organizations. Reports (e.g., reports to donors on quantities of relief items delivered for a given operation) are typically done manually and contain a fairly limited amount of information. Consequently, few performance and/or what-if analyses can be easily performed.

This lack of information and decision technologies indicates that the development of customized decision support models could help address several of the challenges and deficiencies identified in the literature.

Research Objectives

Overall, the purpose of this thesis is to help address the challenges faced by humanitarian relief logisticians through the development of a series of quantitative decision models. Specifically, the present work is aimed at accomplishing the following three research objectives.

- In the first study, the objective is to help decision makers in small development aid organizations manage volunteers more efficiently and effectively. For this purpose, we present a multicriteria scheduling model to support the assignment of volunteer labor in long term development aid.

- In the case of the second study, the objective is to help address some of the volunteer management challenges faced by humanitarian organizations in a humanitarian relief effort. For this reason, we develop a multicriteria scheduling model to support the management of volunteers in relief scenarios that incorporates basic fuzzy logic notions and efficiency analysis in order to better represent the decision maker's knowledge and preferences.
- The objective of the third study is to help decision makers manage the uncertainty inherent to the humanitarian procurement process in a post-disaster recovery situation. For this purpose, we present a stochastic multistage decision model to improve the procurement of goods in humanitarian relief scenarios.

Contributions

As discussed in previous sections, the field of humanitarian logistics represents a relevant domain for supply chain management that has received little attention. This thesis is based on the belief that concepts and tools from the field of logistics and the decision sciences can be enhanced to improve the performance of humanitarian organizations. Thus, one of the planned contributions of this thesis is to help close the gap between qualitative and quantitative research in humanitarian supply chain management through the development of a series of quantitative decision models.

As indicated, we introduce two multicriteria scheduling models to support the assignment of volunteers in humanitarian operations. While employee scheduling has been the topic of extensive research over the past decades in the business literature, no work has focused on the problem of optimizing the assignment of volunteers in humanitarian contexts.

The first model focuses on humanitarian aid for long term development. In this study, we discuss the implementation of the proposed model in a humanitarian aid organization of a South American developing country. We compare the performance of the current approach versus our proposed model, and show how the proposed model can help reduce undesired assignments, task labor shortages, and operating costs.

The second model is focused on volunteer scheduling in humanitarian relief organizations. The multicriteria nature of volunteer management in humanitarian relief efforts is particularly relevant. On the one hand, humanitarian organizations need to manage volunteers wisely so that they become a renewable resource. On the other hand, these organizations need to keep shortages to a minimum in order to increase the effectiveness of their efforts. Our study thus shows how alternative solution methodologies can be used to better represent the decision makers' knowledge and preferences and allow them to deal with those conflicting objectives .

The third model is focused on the procurement process of humanitarian relief organizations. Despite the prevalence of procurement expenditures in humanitarian efforts, the existing humanitarian logistics literature has focused on facility location, inventory management, and transportation. To date, procurement in humanitarian relief has not been based upon scientific methodology. For this reason, we develop a stochastic multistage decision model to improve the procurement of goods in humanitarian operations.

This thesis, thus, presents three new decision models for humanitarian logistics professionals. Overall, the models developed will provide decision makers in the field of humanitarian logistics with approaches for making scheduling and procurement decisions more efficiently and effectively. The thesis will also provide researchers in supply chain and operations management with new alternatives to compare and contrast decision making in humanitarian and commercial systems.

Structure of the Dissertation

This chapter presented background information related to the field of humanitarian logistics. Different challenges faced by humanitarian organizations were discussed and the objectives of this thesis were presented.

Chapter Two provides a detailed discussion of the problem domain and the corresponding literature, and it reviews the state of the art in the area of humanitarian logistics in order to establish the contributions of this research.

Chapters Three, Four and Five introduce the three quantitative decision models for humanitarian logistics. The chapters are structured as three separate but related papers written with the intent of publishing each in the future as an individual journal article in the field of logistics and/or quantitative decision modeling. Chapter Three presents the scheduling model developed to support the management of volunteers in humanitarian relief efforts. Chapter Four introduces the scheduling model for volunteers in long term development humanitarian aid. Chapter Five presents the model to improve the procurement of goods and services in humanitarian relief.

The last chapter, entitled Summary and Conclusions, provides a summary of the research results and findings, as well as a discussion of the limitations and future enhancements to the models developed in the previous chapters.

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CHAPTER 2

LITERATURE REVIEW

Chapter 2

Literature Review

The purpose of this chapter is to provide a detailed discussion of the problem domain and to review the state of the art in the area of humanitarian logistics in order to establish the contributions of this research within the current literature.

The remainder of the chapter is organized as follows. We first provide a general overview of the humanitarian logistics field and characterize humanitarian supply chains and humanitarian supply chain management. Next, we discuss the field of volunteer management and review labor scheduling models. In the next section, we provide an introduction to the field of humanitarian resource procurement. Finally, we provide a general overview of different decision modeling tools available to decision makers in the field of humanitarian logistics.

Humanitarian Logistics

In the supply chain literature, the topic of humanitarian logistics emerged a few years ago and recently has become more widely recognized. Supply chain management in the context of humanitarian organizations has been discussed by Thomas (2003), Beamon (2004), Thomas and Kopczak (2005), Oloruntoba and Grey (2006), and Kovács and Spens (2007), among others. Despite the increasing number of papers published on humanitarian logistics, there has been little application of quantitative modeling techniques to the topic; in general, most papers have simply provided qualitative insights into the problem.

Humanitarian Supply Chain Management

Supply chain management integrates the design, planning and control of material, information and financial flows along the entire value chain from the raw material stage to the point of final consumption. Thomas and Kopczak (2005) defined *humanitarian supply chain management* as the process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from the point of origin to the point of consumption for the purpose of alleviating the suffering of vulnerable people.

Humanitarian supply chain management includes activities that are primarily directed towards promoting human welfare. Humanitarian organizations engage in two main types of activities: relief activities and development aid activities. Relief activities represent short-term activities focused on providing goods and services to maximize recovery from natural and man-made disasters. Development aid activities, on the other hand, include longer-term activities focused on such goals as reducing poverty and improving education.

Overall, the humanitarian arena represents a sector where organizations engage in billions of dollars worth of relief and development aid activities per year. Logistics in the humanitarian sector encompasses several traditional activities such as the procurement, transportation and warehousing of goods and services, as well as other specific activities such as disaster preparedness and planning (Thomas and Kopczak 2005). The next section describes the basic characteristics of humanitarian supply chains.

Humanitarian Supply Chains

As depicted in Figure 2.1, a humanitarian supply chain supports the social mission of a humanitarian organization by managing different types of flows among the participants.

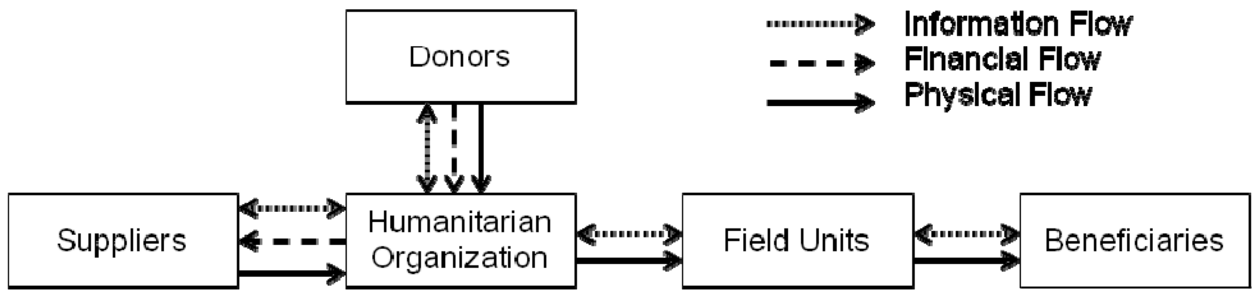

Figure 2.1: A typical humanitarian supply chain

The supply network connects the different stakeholders which include suppliers, donors, humanitarian organizations, and beneficiaries. In addition, the supply chain requires the design and coordination of three main types of flows: Material flows, information flows, and financial flows (Kleindorfer and Van Wassenhove 2004).

Material flows represent physical flows from donors and suppliers to the beneficiaries (there may be reverse flows for recycling purposes, for example, which are not included in the figure above). The type of supplies associated with material flows can be grouped into four main categories: water supply and sanitation, food and nutrition aid, shelter, and health services (TheSphereProject, 2004). Information flows include the transmission and tracking of orders, as well as the transmission of reports from the humanitarian organizations to the donors. Financial flows, on the other hand, represent donations, credit terms and payment schedules (Kleindorfer and Van Wassenhove 2004).

Differences Between For Profit and Humanitarian Organizations

There are a number of differences between humanitarian and for profit organizations that can help illustrate what characteristics make humanitarian decision models different from traditional business models. Based on the work by Moore (2000), we can identify the mission of for profit and humanitarian organizations as one of the key differences. In the case of for profit organizations, the ultimate goal is to make profits in order to maximize the shareholders wealth. In the case of humanitarian organizations, on the other hand, the goal is to achieve their social mission (i.e., to promote human welfare and to alleviate suffering). Moore explains that even though not for profit organizations need financial resources in order to achieve their social missions, the ultimate goals are not financial in nature.

The author also analyzes the primary source of revenues as being one of the main differences between nonprofit and for-profit organizations. In for profit organizations, revenues are earned by selling products and services. In the humanitarian case, however, organizations obtain revenues by attracting charitable contributions from donors and governments. Those contributions can also include in-kind donations of volunteer time and materials, which can help humanitarian organizations reduce operating costs.

The third difference analyzed by Moore is related to performance measurement.
As pointed out by Beamon and Balcik (2008), performance measurement in for profit organizations is more straightforward, since financial measures are clear indicators of performance. Thus, financial bottom lines or equity values are two appropriate measures of performance in for profit organizations. On the other hand, additional challenges exist in the case of humanitarian performance measurement. In this case, performance measurement entails

determining the efficiency and effectiveness in achieving the organizational mission (Moore 2000). The nonprofit literature has addressed several of those issues (See, for example, Speckbacher (2003), Parhizgari and Gilbert (2004), Micheli and Kennerly (2005)). The intangibility and/or immeasurability of their missions, as well as the unpredictable outcomes of their efforts are some of the challenges discussed by Beamon and Balcik (2008).

Overall, the characteristics discussed above require model formulations for humanitarian organizations that are intrinsically different from traditional business decision models, as we will show in the next three chapters.

Differences Between For Profit and Humanitarian Relief Supply Chains

From a supply chain perspective, there are some important differences between humanitarian relief supply chains and commercial supply chains that need to be discussed. As mentioned in the previous section, the main strategic goal is different: The goal of alleviating suffering replaces the profit motive characteristic of commercial supply chains.

Another distinction is related to the type and nature of demand. Demand patterns are relatively less stable and less predictable in the case of humanitarian relief organizations. Demand is typically generated from random events and is unpredictable in terms of location, type and size. Ratliff (2007) also pointed out that humanitarian relief supply chains need to be designed and executed in shorter periods of time.

In terms of inventory management, for-profit supply chains usually have well-established policies based on lead times, demand levels and desired customer satisfaction rates. On the other hand, inventory management in humanitarian supply chains is affected by unreliable, incomplete or non-existent information about lead times, demand levels and locations (Beamon 2004).

Humanitarian relief supply chains present some additional differences. With respect to the configuration of the distribution network, the number and location of distribution centers is usually not known with certainty in the case of relief chains. The same considerations apply to the financial flows. The flow of finances within humanitarian relief supply chains is different since relief efforts are in large part funded by donations that occur after a disaster event. In addition, changes occur fast and cannot be predicted in advance. Ultimately, the social and political environment in which these supply chains need to operate does nothing but increase the level of uncertainty.

Humanitarian Volunteer Labor

As mentioned in the previous chapter, in this thesis we introduce two multicriteria scheduling models to support the assignment of volunteers in humanitarian operations. Accordingly, our review of the literature will focus on past volunteer management and workforce scheduling research.

Volunteer Management

Volunteer management research is a fairly mature topic in the social sciences. Researchers in the field of economics, for example, have developed econometric models to measure and study the supply and demand of volunteers (Freeman 1997; Segal and Weisbrod 2002; Hackl and Pruckner 2006). The different areas of volunteer management that have been researched include the motives for volunteering, i.e, the reasons why people volunteer (Cnaan and Goldberg-Glen 1991; Allison, Okun et al. 2002; Bussell and Forbes 2002). Opportunities for personal growth, recognition, achievement, and a desire to contribute to the community are some of the incentives for volunteering cited by past research. Another topic that has been studied in the past involves the demographic characteristics of volunteers, such as education and gender, and their relationship to present and future commitment levels (Lammers 1991; Van Vianen 2008).

The area of volunteer retention and the analysis of what practices encourage renewed volunteerism and why people continue to volunteer is also an important topic (Gidron 1984; Hager, Brudney et al. 2004). Some of the management practices that positively influence the retention of volunteers include recognition activities and matching volunteers to appropriate tasks. Gidron (1984), for example, cites task achievement and the quality of the work itself as some of the variables that could better predict volunteer retention.

Each of these areas of research will play an important role in the development of our models, as we will be show in Chapters Three and Four.

Labor Scheduling

A large number of articles has been published on labor scheduling. The seminal work by Dantzig (1954) is often considered as the first formulation of a labor scheduling problem. Dantzig’s model involved a set covering formulation that determined the lowest possible cost while satisfying employee requirements for different shifts. Another model that is often considered a seminal work is the one developed by Keith (1979). The author presented a formulation which allowed deviations from employee requirements. In his model, deviations from the target values labor requirements were penalized. The works by Dantzig and by Keith provided the basis for most labor scheduling research.

Minimization of wage costs has historically been the most popular objective in labor scheduling. However, throughout the years different authors have considered alternative objectives in their formulations. In this sense, the consideration of employee preferences in scheduling models (e.g., Miller, Pierskalla et al. (1976) and Warner (1976)) is regarded as another major contribution to the field.

The existing work on labor scheduling can generally be categorized by solution methodology, by type of model and by application area. Relevant reviews of the state of the art include Alfares (2004) and Bechtold et al. (1991), among others.

With respect to solution methods and techniques, it has been noted that the literature is heavily skewed towards mathematical programming approaches (Ernst, Jiang et al. 2004). Due to the size of many scheduling problems, a number of different heuristic methods have also been developed (see, for example, Goodale and Thompson (2004)). In the case of our chosen applications, we will use a spreadsheet based solver to generate optimal solutions to our scheduling problems.

There are four types of models that are relevant to volunteer labor problems: Days off scheduling models deal with determining the off-work days for each worker over the planning horizon. Shift scheduling, on the other hand, is used to determine employee schedules over a daily planning period, while tour scheduling deals with identifying how many employees assume certain shift schedules. This type of model is the most prevalent in the literature (Sampson 2006). The fourth type, tour assignment, specifies both shifts and job assignments for each individual worker over the scheduling period. Since in our models we want to consider volunteer preferences for both shifts and locations (Chapter 3) as well as time blocks and tasks (Chapter 4), we will need to develop a tour assignment model.

From an application perspective, the operations research/management science (OR/MS) literature includes several different application areas related to labor assignment problems. Since their inception, scheduling and staffing methods have been applied to areas ranging from airline crew staffing (Kohl and Karisch 2004) to nurse scheduling (Azaiez and Al Sharif 2005; Parr and Thompson 2007).

In the disaster management field, Janiak and Kovalov (2006; 2008) studied scheduling problems where tasks need to be executed by human resources in areas contaminated with radio-active materials. In their model, the authors studied single worker problems with the objectives of minimizing maximum lateness or total weighted completion time. The idea of modeling individual volunteer preferences, for example, was not considered. Another somewhat related article by Metters and Vargas (1999) discusses issues related to nonprofit organizations from a quantitative decision modeling perspective. The authors extended yield management concepts to the nonprofit sector by developing a heuristic to assist in pricing decision making. Their technique was demonstrated at a nonprofit child care center. One of the key attributes of their model is the idea that profit maximization is not the most important goal for nonprofit organizations.

As discussed above, several articles have been published on labor scheduling as the topic has become gradually more important due to the prevalence of the services sector in the economy. However, the scheduling of volunteers, in general, has not been extensively discussed in the operations research literature. More specifically, a review of the literature related to labor scheduling research with a focus on non profit or volunteer applications resulted in only two specific articles.

The first of these two articles, by Gordon and Erkut (2004), developed a spreadsheet-based model to schedule volunteers for a music festival. Although, as in our current research, the authors used an integer programming formulation to incorporate user preferences and constraints into the model, they did not explicitly consider the issue of labor shortages. Labor shortages need to be explicitly considered in the case of small development aid organizations, such as the one analyzed in Chapter 3, because these organizations typically rely heavily on a small number of volunteers with limited time availability. By incorporating labor shortages into the model, we can, for example, help the decision maker balance those shortages among shifts.

In the second of the two articles, Sampson (2006) developed an integer goal programming model for volunteer labor assignments in the context of reviewers for an academic conference. Our current research differs from that of Sampson in that we do not assume that volunteer labor costs are negligible. As we will see in the next chapter, some development aid organizations pay allowances in order to offset costs (such as travel expenses) incurred by their volunteers. In addition, from an application perspective, while labor assignment problems have been the topic of extensive research in the business literature, no work has focused on the problem of optimizing the assignment of humanitarian aid and relief volunteers, the topics of Chapters Three and Four, respectively.

Humanitarian Resource procurement

The third model in this thesis is focused on the procurement processes of humanitarian relief supply chains. The relevance of this topic cannot be underestimated. Each year, humanitarian organizations from different parts of the world implement a wide variety of efforts aimed at recovering from disasters and reducing poverty, and in the process they procure an estimated US$ 50 billion worth of goods and services from local and international suppliers, with the procurement of goods representing around 60% of all those expenditures (Taupiac 2001). Blecken and Hellingrath (2008), for example, estimate that procurement accounts for 65% of all expenditures in disaster relief logistics.

However, despite the prevalence of procurement expenditures in humanitarian efforts, no previous work has focused on humanitarian relief procurement. The existing humanitarian logistics literature has been focused on facility location, inventory management, and transportation problems but not on procurement ones. The following list provides a brief overview of previous humanitarian relief logistics research (A more detailed review of the existing literature is presented in Chapter Five):

- The inventory management literature in the context of humanitarian relief operations includes papers such as the one by Beamon and Kotleba (2006), in which the authors describe the development of a humanitarian relief inventory model to determine optimal order quantities and re-order points for relief warehouses.
- Facility location research includes the work by Akkihal (2006), who developed a mixed-integer linear program to determine facility configurations where the objective is to minimize the average global distance to the victims. Balcik and Beamon (2008), on the other hand, integrated facility location and inventory decisions in humanitarian relief contexts. The authors introduced a mixed-integer linear program to determine not only the number and location of distribution centers in a relief network but also the amount of relief supplies to be stocked at each distribution center in order to meet the needs of people affected by the disasters.

- The literature related to the transportation and delivery of goods in humanitarian relief chains also presents a number of relevant applications. For example, Barbarosoglu et al. (2002) developed a mixed integer mathematical programming model for aerial transportation during a disaster relief operation.

Procurement in the Business Sector

Since no previous work has focused on humanitarian relief procurement, we now proceed to analyze procurement models from the business sector. Procurement decisions typically consist of determining the best mix of suppliers in order to allocate orders among them and satisfy a wide variety of decision criteria (Aissaoui, Haouari et al. 2007).

Past procurement research can be classified into single item procurement models (Buffa and Jackson 1983; Rosenblatt, Herer et al. 1998) and multiple item procurement models (Kasilingam and Lee 1996; Karpak, Kumcu et al. 1999). An alternative line of research has focused on analyzing the impact of quantity discounts offered by suppliers (Austin and Hogan 1976; Crama, Pascual J et al. 2004).

Other researchers focused their efforts on the development of multiobjective procurement models (Ghodsypour and O'Brien 2001; Dulmin and Mininno 2003). The traditional criteria studied by researchers in previous works include total costs and product quality.

Procurement decisions are also subject to a wide variety of constraints. Weber and Current (1993) classify the different procurement constraints into two categories: system constraints, which are defined as those that are not directly under the control of the decision maker, and policy constraints, which are defined as those constraints that the firm can directly influence.

System constraints may include:

- supplier capacities,
- minimum order quantities determined by suppliers, as well as
- price discounts.

On the other hand, policy constraints may include:

- minimum number of suppliers to be selected, and
- maximum amount of business to give to a certain supplier.

This thesis is based on the belief that concepts and tools from the field of logistics can be enhanced to improve the performance of humanitarian organizations. Since a fairly large number of procurement articles has been published in the business literature, our current research effort is aimed at developing a quantitative model for humanitarian procurement that, based on the existing business literature, incorporates some characteristics that are unique to the humanitarian relief sector, such as the impact of donations on procurement budgets. Each of the areas of research discussed above will play an important role in the development of our multiple item humanitarian procurement model, as we will be show in Chapter Five.

OR/MS Modeling for Humanitarian Logistics

As discussed in the previous chapter, a large number of humanitarian problems require that decisions be made in the presence of uncertainty. In those cases, developing optimal solutions can be a very difficult task. Dantzig, for example, considered uncertainty as one of the most important open problems in optimization (Horner 1999). Altay and Green (2006) argue that the randomness of the impacts and problems caused by humanitarian emergencies demand dynamic, real-time, effective and efficient solutions, thus making the topic very suitable for OR/MS research.

A key difficulty in optimization under uncertainty is dealing with a big uncertain solution space that frequently leads to very large-scale optimization models. The difficulty comes from the need to evaluate several random functions and their expectations. Thus, the size of the model grows significantly based on the number of uncertain parameters and the number of possible realizations of those uncertain parameters. Given the computational burden that is created, optimization in the presence of uncertainty can become difficult and computationally expensive for some decision problems (Trosset 2000). As a consequence, practical solutions may require some sort of modeling simplification such as the development of a finite set of scenarios, such as the ones we present in Chapter Five.

Optimization and Uncertainty

Since its origin, optimization has seen numerous developments. There are several different tools for addressing optimization problems in the presence of uncertainty. Along with them, different algorithms have been developed and research has shown that they can be used successfully in many applications. In the end, the type of data available to the decision maker, the assumptions on risk, as well as the problem structure and properties are what determine which tool to use.

The different tools available for addressing optimization problems in the presence of uncertainty are: chance-constrained stochastic programming, robust stochastic programming, stochastic dynamic programming, recourse-based stochastic programming, and fuzzy programming. These different optimization tools, along with their uses, advantages and disadvantages are briefly reviewed next.

Chance-constrained stochastic programming

The focus in chance-constrained stochastic programming is to achieve feasibility in an uncertain environment by adding probabilistic or chance constraints. Prekopa (1995) discusses different procedures along with potential complications. One potential issue of this approach is that the feasible set may be non-convex. In the disaster management literature, for example, Papamichail and French (1999) used constraint programming to develop feasible evacuation strategies in the case of nuclear emergencies.

Robust stochastic programming

Traditional stochastic models are based on the assumption that the decision-maker is risk-neutral. For those cases where this assumption cannot be made, the idea of risk was incorporated into stochastic programming (Mulvey, Vanderbei et al. 1995). Different applications of robust stochastic programming have been reported, but some researchers have demonstrated that robust models may result in solutions that are suboptimal (e.g., Sen & Higle (1999)).

Stochastic dynamic programming

This tool is suitable for multistage stochastic decision processes. In this method, the original problem is solved at the last step of the process by utilizing the solutions of all the sub problems. This tool is very computationally intensive because all sub problems must be solved first. There are also dimensionality issues as the computational time grows exponentially with more complex decision problem. However, there are a number of approximation techniques that can be used to reduce the impact of those issues. For example, neuro-dynamic programming algorithms can be used to obtain solutions for dynamic programming problems (e.g. Bertsekas & Tsitsiklis (1996)).

Recourse-based Stochastic Programming

In the recourse-based stochastic programming approach, the decision variables of an optimization problem under uncertainty are divided into different stages. In the two-stage case, for example, the first stage variables need to be decided before the actual realization of the uncertain parameters. The objective in this case is to select the first-stage variables such that the sum of first-stage costs and the expected value of the random second-stage costs are minimized. Two-stage stochastic linear programs are the classical stochastic programming modeling paradigm, but the discipline of stochastic programming has grown and been expanded to other cases and solution approaches. We can sub classify stochastic programs into linear, integer, and non-linear models.

- **Stochastic Linear Programming:** The most widely used stochastic programming models are two-stage linear programs. This tool allows the decision maker to take some action in the first stage, after which a random event occurs. Next, a recourse decision is made in the second stage to compensate for any "bad" outcomes. The simplicity of this model allows the decision maker to solve the problem as a convex program with linear constraints. For an extensive discussion of stochastic linear programming, one can review standard textbooks on stochastic programming such as Birge et al. (1997).

- **Stochastic Non-linear Programming:** If linearity cannot be assumed, then the decision maker should look at the non-linear case. This area of modeling deals with non-linear versions of the linear and integer cases. Non-linearities, however, may give rise to non-convexities and local optima. Furthermore, in the case of integer and non-linear problems one needs to decide which problem-specific algorithm to use.
- **Stochastic Integer Programming:** This tool should be considered when facing a decision problem that can be represented as a linear program where some of the variables are constrained to take only integer values. Klein Haneveld et al. (1999) provide relevant information related to properties and algorithms for stochastic integer programming models. In Chapter 5 we will discuss how this type of model can help address the need for adjusting the decision-making process under conditions of extreme uncertainty. Furthermore, we will develop a two-stage model with mixed-integer recourse for procurement in humanitarian relief supply chains.

Overall, two-stage stochastic programming with recourse has been successfully applied to the study of different relief chain activities. Since our work is most closely related to those authors that developed two-stage programs, a few examples are presented next, while a more detailed review of the literature on this topic is presented in Chapter Five.

Viswanath et al. (2002), for example, focused on the transportation aspect of disaster relief and developed a two-stage stochastic integer program with recourse for the disaster-related problem of investing in the links of a network to improve its expected post-disaster performance. Along the same line of research, Barbarosoglu and Arda (2004) developed a two-stage stochastic programming model to plan the transportation of vital first-aid commodities to disaster-affected areas during emergency response. Tean (2006) combined transportation and facility location considerations and developed a two-stage stochastic optimization model to assist in the pre-positioning of relief units and assets.

Procurement in humanitarian contexts, however, has not been based upon scientific methodology. Specifically, our work extends the existing recourse-based stochastic programming body of knowledge by developing a model that will allow humanitarian relief logisticians to find the optimal quantities of relief items to order from the different available suppliers at each stage.

Fuzzy Logic

Fuzzy programming is another tool available for addressing optimization problems in the presence of uncertainty. Fuzzy logic is a form of mathematics that can be used to represent imprecision in the variables of a mathematical model. Zadeh (1965) first introduced the use of fuzzy relationships (known as fuzzy sets) to represent vague and/or imprecise concepts. From that point onwards, fuzzy logic has developed into a very robust and widely applied approach for concept representation.

As mentioned above, this approach provides a formalized framework for dealing with the imprecision intrinsic to many decision problems. Many decision-making situations such as disaster relief scenarios are too complex to be represented using precise quantitative information. Nevertheless, a decision maker may be able to use knowledge that is imprecise in order to arrive to a solution. In this sense, fuzzy logic resembles human reasoning in its use of approximate information to model decisions. Since knowledge can be represented in a more natural way by using fuzzy sets, many decision situations can be greatly simplified.

Fuzzy Sets and Fuzzy Membership Functions

In traditional mathematics, elements have crisp values. In fuzzy logic, elements do not have precise values, but rather relate a variable to a grade of membership in a set of values. For example, a variable called “generous donation” would have different grades of membership. The values in those sets would be subjective and vary from decision-maker to decision-maker, *i.e.* one organization might consider $10,000 as a generous donation, while another organization might not. In order to represent the variable “generous donation” as a fuzzy set, the decision-maker should associate a grade of membership with a particular donation amount. Figure 2.2 below presents a possible relationship between donation amounts and grades of membership for the linguistic variable “generous donation”.

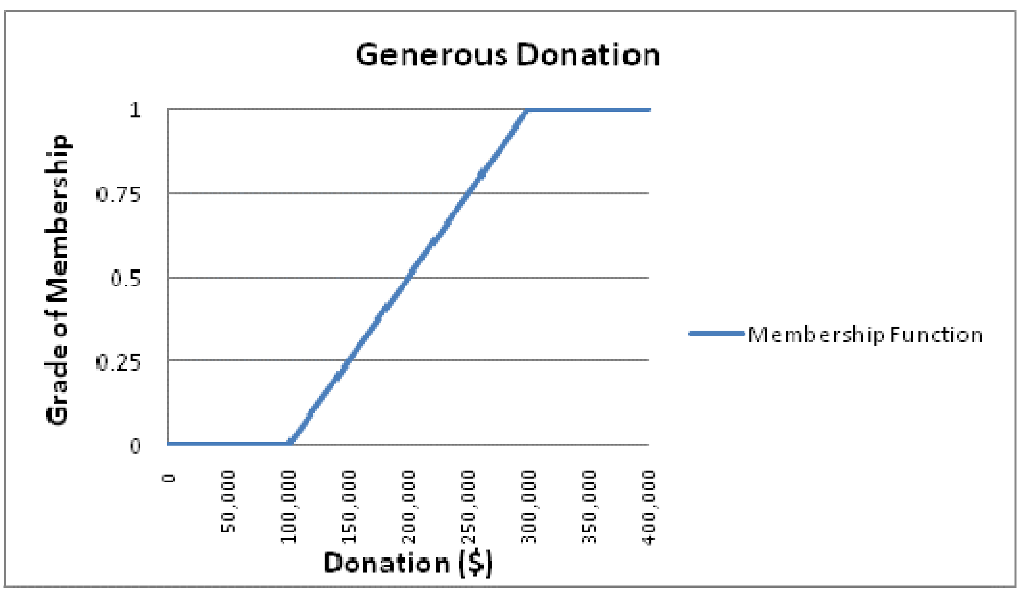

Figure 2.2: “Generous Donation” membership function

As shown in Figure 2.2, grades of membership range from zero to one. A grade of zero would indicate that a particular value does not 'belong' to the set, while a grade of one would indicate that the value is a 'full member' of the set. In the example above, a donation of $300,000 or more would receive a grade of membership of 1 in that particular fuzzy set. Fuzzy sets can thus be represented by a function that relates each value to a grade of membership. Such a function is known as a Membership Function. Membership functions are built based on subjective preferences and are, therefore, dependent on the decision maker and the problem situation.

Fuzzy programming

In the case of fuzzy programming, uncertainty is modeled using fuzzy numbers and fuzzy sets (such as the ones we just described) rather than discrete or continuous probability functions. This approach is most appropriate for decision-making problems where knowledge and preferences cannot be represented using precise quantitative information, e.g. if we have linguistic terms. There are different types of fuzzy programming applications for different decision making problems. For example, fuzzy logic can be used to deal with right-hand side uncertainties (Zimmermann (1991)) or to model uncertainties in the objective function coefficients as well as in constraints coefficient (Tanaka & Asai (1984)). A key benefit of this approach is that fuzzy sets with linear membership functions can be used extensively. In the volunteer management model we present in Chapter Four, the different objectives for potential schedules will be defined as linear fuzzy sets.

Even though the use of linear functions may sound like a poor approach to model decision-makers' preferences, it has been demonstrated that the optimal solution obtained using linear membership functions is practically the same as the solution obtained using complicated non-linear membership functions (Delgado, Herrera et al. 1993). Some of the disadvantages of this approach (and of fuzzy logic in general) are that it might be difficult and cumbersome to estimate several different membership functions, and that results will vary based on the different approaches that are used to combine the fuzzy sets. Nevertheless, Chapter Four will show how a fuzzy approach could be used as a decision support tool for decision makers in the context of disaster relief.

Throughout this chapter we discussed several important aspects related to the field of humanitarian logistics. We first characterized humanitarian supply chains and humanitarian supply chain management, and then we reviewed the application areas that will be the focus of this thesis. Specifically, we examined the field of volunteer management and reviewed labor scheduling models. We also took a look at humanitarian procurement and discussed a series of modeling alternatives. Finally, we presented a general overview of the decision modeling tools that will be used in different parts of this thesis. The next three chapters present our proposed models.

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CHAPTER 3

HELPING A SMALL DEVELOPMENT AID ORGANIZATION MANAGE VOLUNTEERS MORE EFFICIENTLY

Chapter 3

Helping a Small Development Aid Organization

Manage Volunteers More Efficiently

Abstract

Development aid organizations plan and execute efforts that are primarily directed towards promoting human welfare. Because these organizations rely heavily on the use of volunteers to carry out their social mission, it is important that they manage their volunteer workforce efficiently. In this study, we discuss the development of a spreadsheet-based multicriteria scheduling model for a small development aid organization in a South American developing country. We demonstrate not only how the proposed model helps to reduce the number of unfilled shifts and to decrease total scheduling costs, but also how it helps to better satisfy the volunteers' scheduling preferences, thus supporting long-term retention and effectiveness of the workforce.

Keywords

Development Aid, Multicriteria Decision Making, Optimization, Scheduling, Spreadsheets, Volunteer Labor

Introduction

All over the world, thousands of development aid organizations plan and execute efforts that are primarily directed towards promoting human welfare. These development aid organizations rely heavily on the use of volunteers to carry out their social mission. As a consequence, it is important for development aid organizations to manage efficiently their volunteer workforce in order to successfully retain their volunteer bases. While employee scheduling has been the topic of extensive research over the past decades in the business literature, we are aware of no work that has focused on the problem of optimizing the assignment of development aid volunteers.

In this study, we discuss the development of a multicriteria scheduling model for a small humanitarian aid organization operating in a South American developing country. We compare the performance of the current scheduling approach versus that of our proposed model, and show how the proposed model helps reduce the number of undesired assignments, labor shortages, and total schedule costs. The remainder of the paper is organized as follows: First, we present an overview of the fields of labor scheduling and spreadsheet decision modeling. We then provide a description of the problem, followed by a discussion of the proposed model and an analysis of the results. Finally, we conclude with a discussion of the lessons learned from our research study.

Labor Scheduling

A large number of articles has been published on labor scheduling. The existing work on labor scheduling can generally be categorized by type of model, by solution methodology, and by application area. Relevant reviews of the state of the art include Alfares (2004) and Bechtold et al. (1991), among others. With respect to solution methods and techniques, it has been noted that the literature is heavily skewed towards mathematical programming approaches (Ernst, Jiang et al. 2004). Due to the size of many scheduling problems, a number of different heuristic methods have also been developed (see, for example, Goodale and Thompson (2004)). In the case of our chosen application, the small size of the organization under study allows for the use of a spreadsheet based solver to generate an optimal solution to the scheduling problem.

The operations research literature includes several different application areas related to labor assignment problems. Since their inception, scheduling and staffing methods have been applied to areas ranging from airline crew staffing (Kohl and Karisch 2004) to nurse scheduling (Azaiez and Al Sharif 2005; Parr and Thompson 2007). However, the scheduling of volunteers, in general, has not been extensively discussed in the operations research literature. A review of the literature related to labor scheduling research with a focus on non profit or volunteer applications resulted in only two specific articles.

The first of these two articles, by Gordon and Erkut (2004), developed a spreadsheet-based model to schedule volunteers for the annual Edmonton Folk Music Festival. Although, as in our current research, the authors used an integer programming formulation to incorporate user preferences and constraints into the model, they did not explicitly consider the issue of labor shortages. Labor shortages need to be explicitly considered in the case of small development aid organizations, such as the one analyzed in our study, because these organizations typically rely heavily on a small number of volunteers with limited time availability. By incorporating labor shortages into the model, we can, for example, help the decision maker to balance those shortages among shifts.

In the second of the two articles, Sampson (2006) developed an integer goal programming model for volunteer labor assignments in the context of reviewers for an international academic conference. Our current research differs from that of Sampson in that we do not assume that volunteer labor costs are negligible. As we will see in the next section, some development aid organizations pay allowances in order to offset costs (such as travel expenses) incurred by their volunteers. Overall, while labor assignment problems have been the topic of extensive research in the business literature, no work has focused on the problem of optimizing the assignment of development aid volunteers.

Spreadsheet Decision Modeling

Spreadsheets have become one of the most popular and ubiquitous software packages. Indeed, some researchers have noted that managers often become so comfortable with spreadsheets that they are reluctant to adopt other software packages; even if the other packages are more suitable for specific applications (Chan and Storey 1996). Advances in spreadsheet analytical ability have made various decision modeling techniques accessible to all types of organizations. Different authors have reported successful developments of spreadsheet-based decision models for a variety of business and non-profit organizations (Gordon and Erkut 2004; LeBlanc and Galbreth 2007; Farasyn, Perkoz et al. 2008; Pasupathy and Medina-Borja 2008).

Given the modeling power offered by spreadsheets, and the relatively low cost of acquiring and using them, spreadsheets represent a very good platform for delivering Operations Research/Management Science (OR/MS) solutions to organizations in developing countries. Business disciplines such as finance have been successful in creating different instruments for poverty reduction in developing countries. For example, several researchers have analyzed the impact of Microcredit programs (i.e., programs that provide very small loans to low-income people in impoverished areas) to combat poverty and foster long term development (Diniz, Pozzebon et al. 2009; Gurses 2009; Knight, Hossain et al. 2009). In much the same way that these Microcredit programs can significantly improve the lives of the people they serve, we believe that "Micro-OR" models, implemented within spreadsheets and focused on helping small organizations in developing countries, can also have a significant, beneficial impact at the local level. This paper provides an example of one such Micro-OR application.

Description of the Problem

The subject of our study is a small development aid organization that provides youth counseling in low income neighborhoods of a South American developing country. The organization has between 20 and 25 active volunteers who can be assigned to two different centers. Volunteer work is done during the weekends. Figure 3.1 summarizes the organization's shift structure. There are two shifts on Saturday and Sunday: the morning shift (between 9:00am and 1:00pm) and the afternoon shift (between 1:00pm and 5:00pm). On Fridays, volunteers work only in the afternoons.

Shift	Time		Friday	Saturday	Sunday
Morning	9:00	10:00			
	10:00	11:00			
	11:00	12:00			
	12:00	13:00			
Afternoon	13:00	14:00			
	14:00	15:00			
	15:00	16:00			
	16:00	17:00			

Figure 3.1: Graphical display of the organization's shift structure. Volunteer work is done during the weekends only.

The current scheduling approach is as follows: once a week, volunteers submit their preferences and they are assigned to shifts and centers on a first-come, first-served basis. The schedule is built by hand which not only represents a time-consuming task for the person in charge of the scheduling process but also results in sub-optimal solutions.

The organization has different policies related to the management of their volunteers. For example, the organization has rules that are used to determine the maximum number of shifts that a volunteer should be assigned to. Not surprisingly, the schedules developed by the organization usually fail to satisfy these constraints. The manual approach also makes it difficult to balance shortages among the different shifts, and, as a result, the different policies are ignored or violated on a regular basis.

An additional source of inefficiency in the scheduling process is related to the payment of a *per diem* to each scheduled volunteer in the organization. Volunteers receive one *per diem* to offset any travel expenses they may incur regardless of whether they work one or two shifts on any given day. The organization thus has an opportunity to save resources by assigning, whenever possible, the same volunteer to the morning and afternoon shift instead of assigning two different volunteers, one to the morning shift and the other one to the afternoon shift.

Proposed Solution

In order to overcome the inefficiencies mentioned above, we developed a multicriteria scheduling model with binary and general integer variables to manage the assignment of volunteers. The multicriteria nature of the problem is extremely relevant. On the one hand, development aid organizations need to manage volunteers wisely so that they become a renewable resource. On the other hand, these organizations need to keep shortages to a minimum in order to increase the effectiveness of their efforts. The design of the different components of our model is discussed next, while a detailed model formulation is included in the Appendix.

Defining the Objectives

The objectives of the organization were determined to be the following:

- to reduce the number of undesired volunteer labor assignments,
- to reduce volunteer labor shortages, and, if possible,
- to reduce operating costs.

Taken together, these three objectives contribute towards the overall mission of promoting human welfare while using the available human and financial resources efficiently and effectively. In our model, the three objectives mentioned above were structured as follows.

- *Fairness:* In the case of the first objective, we are interested in minimizing the number of undesired assignments so that volunteers' preferences are honored as much as possible. For this purpose, the model takes into consideration individual shift and center preferences (e.g., volunteers may request to have a certain day or shift off or they may request to be assigned to a specific center). Undesired assignments are calculated by having each volunteer specify where and when they would rather be assigned and then by minimizing the number of assignments that were not requested by them in the first place.

- *Labor Shortages:* In the second objective, we want to minimize labor shortages. Shortages occur when the required minimum number of volunteers for a certain shift is not met. The model will then minimize across shifts and centers the sum of all negative deviations from the required minimum number of volunteers.
- *Schedule Costs*: As explained in previous sections, volunteers that are assigned to a shift receive *per diem* allowances. The total schedule costs in our problem are calculated by summing the costs associated with each individual shift assignment. We adjust this calculation to reflect the fact that cost savings can be achieved by assigning the same volunteer to the morning and afternoon, since volunteers receive the same allowance regardless of whether they work one or two shifts on any given day (see equations (1) and (5)).

In order to show the members of the organization how the proposed optimization approach worked, our multicriteria model was first solved as a two-objective problem by removing the third and least important objective (total schedule costs) from the formulation. The two-objective formulation allowed us to demonstrate more effectively the functioning of the optimization model as the simplification made it easier for the decision maker to interpret the tradeoffs between the other two objectives. This also allowed us to better capture input from the decision maker regarding parameters and constraints.

Ultimately, for the sake of simplicity, we decided to develop a weighted rather than a preemptive model. This allowed us to consider the three objectives at the same time and avoid running the model more than one time in order to arrive at a solution. The resulting objective function (equation (1)), minimizes a weighted linear combination of the three objectives discussed above. We decided to express the three objectives as percentages in order to avoid scaling issues. Next, we had to decide how to assign weights to each goal. For this purpose, we discussed the relative importance of the objectives with the organization. Treating volunteers fairly and accommodating their preferences was considered by far the most important objective by them. Total schedule costs, on the other hand, were considered the least important objective. The relationship among the three objectives is formalized in equation (2). Using this information, we incorporated data validation functionality into the spreadsheet-based model to enforce the relationship among the three objectives and ensure that only valid parameters values were entered by the user.

Formulating the model

The solution to the volunteer management problem is the assignment of volunteers to the different shifts at one of the centers. We represent this solution by a set of binary variables that assume a value of one if a volunteer is assigned to a certain shift at a particular center, and a value of zero otherwise. A second set of integer variables represents the shortage of volunteers (in terms of number of persons) for each shift at each center.

There are two other sets of binary variables in the model. The variables in the first set assume a value of one if a volunteer is assigned to one or fewer shifts on a certain day, and assume a value of zero otherwise. The variables in the second set assume a value of one if a volunteer is assigned to both the morning and afternoon shifts in the same day, and a value of zero otherwise. We included these two sets of variables in the model in order to manage *per diems* more efficiently.

As explained above, the organization needs to collect data related to the preferences of the volunteers in order to use the model. We suggested taking into consideration the seniority of volunteers but the organization felt that implementing a seniority policy would affect the chances of retaining the newer members. As a consequence, the preferences of all volunteers receive the same priority in the model.

The organization also needs to specify the available budget for the scheduling period, as well as the *per diem* they will pay each volunteer. A constraint in the model uses those two parameters to enforce that total schedule costs do not exceed the available budget level.

Another step in the development of the model involved translating the different policies into model constraints. With respect to the number of volunteers required per shift, a set of constraints in the model uses this information to ensure that an appropriate number of volunteers is assigned to each shift. A different set of constraints is used to balance shortages among shifts and centers. These constraints use the maximum allowed size of volunteer shortages per shift to limit shortages across all shifts over the scheduling horizon.

Finally, two other sets of constraints place upper limits on the number of shifts a volunteer should work and on the number of undesired assignments. The underlying premise is that volunteers should be treated fairly and that they should not be under or over-worked.

Designing the Graphical User Interface

Because the users of this model are individuals who are more or less familiar with the use of spreadsheets but have almost no knowledge of optimization, the model worksheets and forms were designed to make the data entering procedures, the solution process, and the reporting functionalities as easy to use as possible. A screenshot of the system’s main menu is provided below (Figure 3.2). The system is based on Excel as the software platform, with the addition of Visual Basic for Applications (VBA) for providing additional automation and data analysis capabilities. The ability to augment Excel's capabilities with VBA makes it a powerful and visually interactive modeling environment for building decision support systems.

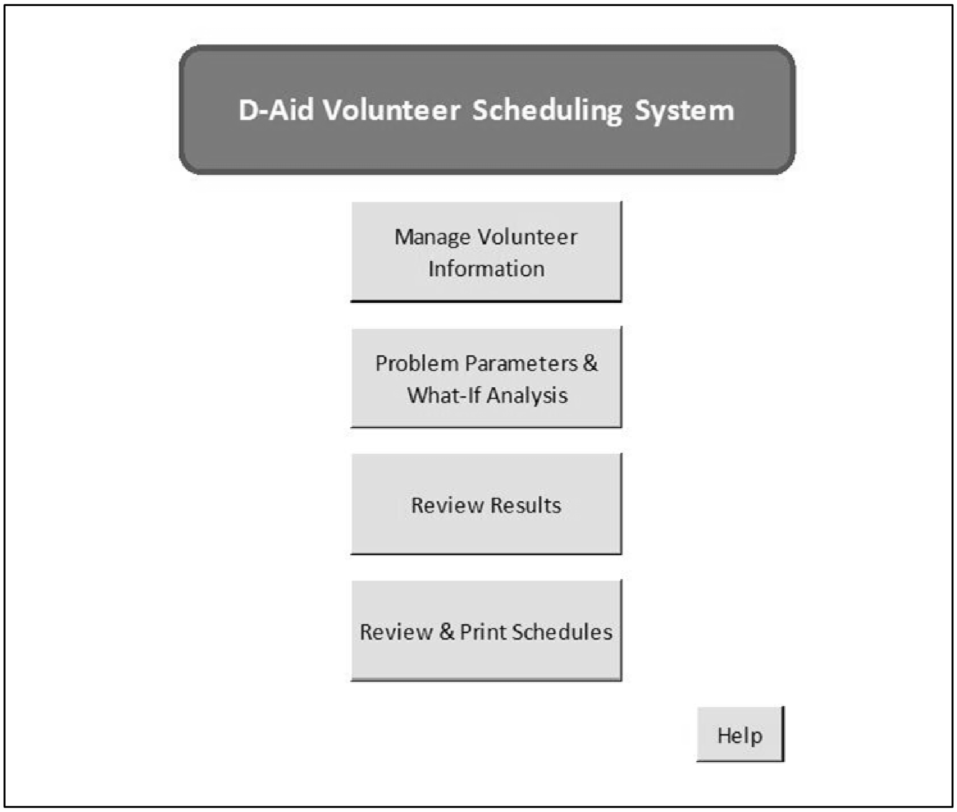

Figure 3.2: Screenshot of the main menu

The major functionalities provided include access to a worksheet where volunteers' contact information as well as their shift and center preferences can be maintained and updated for the current scheduling period. The user can also use the menu to navigate to a worksheet where he/she will need to enter all the different parameters (other than the individual volunteer parameters) described in the Appendix . Data validation functionality is used extensively in this worksheet to enforce the relationships among the parameters and to ensure that only valid values are entered. Once all the parameters are entered, a ‘Solve’ button is used to run a VBA macro that formulates and solves the model. A relevant feature of this worksheet is that it provides the user with what-if functionality, i.e., the user can change any of the parameters and analyze what happens to the values of the three objectives in the optimal solution. For example, Figure 3.3 below displays part of the ‘Parameters’ worksheet and illustrates how the user can easily change any of the objective weights, click on the ‘Solve’ button, and quickly visualize any changes in the optimal solution.

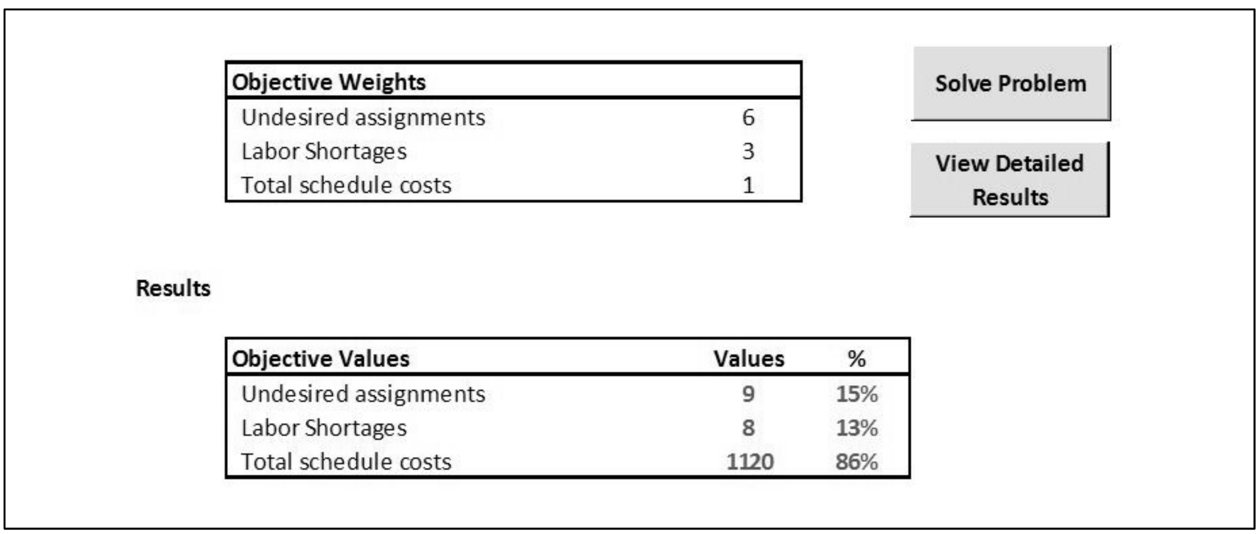

Figure 3.3: The system provides the user with what-if functionality. The decision maker can change any of the parameters and quickly analyze what happens to the values of the three objectives in the optimal solution.

The individual volunteer results are then available, via the menu, on a different spreadsheet where the user can print the results in order to distribute them to the volunteers. Help functionality is also provided to assist with the proper use of the system.

Overall, the user interface provides the organization with an Excel-based decision support tool in a user friendly and straightforward setup.

Results

The final step in the model development process was to test the performance of the spreadsheet-based optimization model in order to measure its impact. For this purpose, the performance of the organization's manual scheduling approach was compared against that of our proposed model.

The data used to compare the two approaches consisted of thirteen periods of volunteer preferences. These preferences were entered into spreadsheets. Next, schedules were developed using both the current scheduling approach (manually assign volunteers on a first-come, first-served basis) and the proposed optimization model, and the results obtained with the two alternative approaches were calculated with respect to the three objectives. Finally, we performed three Paired-Sample hypothesis tests (one for each objective) in order to determine whether there were any statistically significant differences between the performance of the two approaches. Figures 3.4 through 3.6 below compare the results obtained with the currently used approach to those obtained with the optimization model.

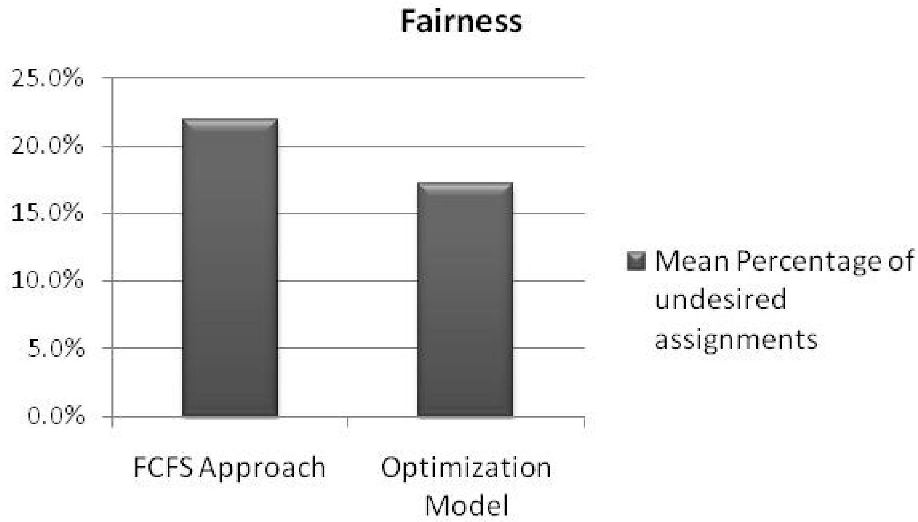

Figure 3.4: Mean results obtained with the two solution methods for the Fairness objective

Treating volunteers fairly and accommodating their preferences was the most important objective for the organization. This objective received the largest weight in the model formulation and, as a consequence, the proposed optimization model was able to reduce undesired assignments by an average of 21.7%. The hypothesis test indicated that the average results obtained with the optimization model for the Fairness objective were significantly lower than the ones obtained with the First-Come, First-Served (FCFS) approach at the 0.05 level of significance (n = 13).

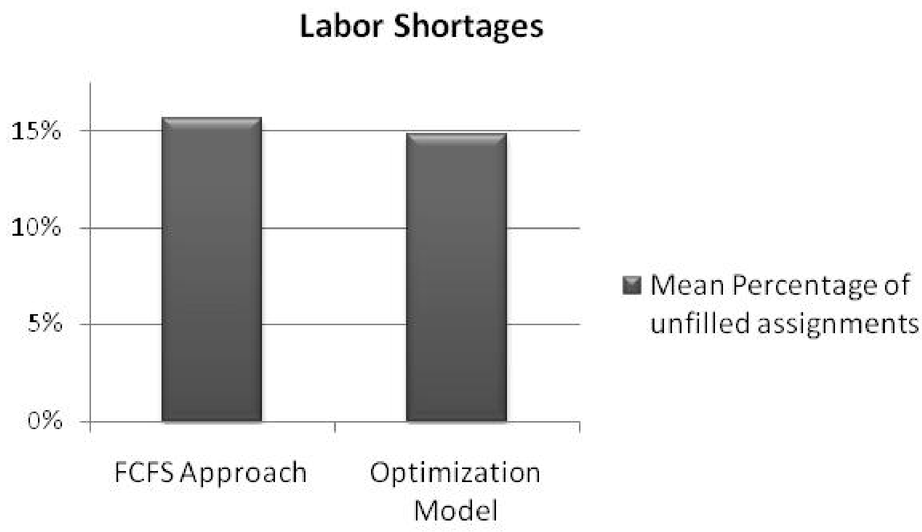

Figure 3.5: Mean results obtained with the two solution methods for the Labor Shortages objective

On the other hand, the percentage of unfilled assignments was reduced, on average, by 5.3%. Shortages were not reduced as much as the number of undesired assignments because the Labor Shortages objective does not receive the same weight in the model formulation. The results of the hypothesis test indicated that there were no statistically significant differences between the two approaches with respect to labor shortages at the 0.05 level of significance.

As discussed before, the organization feels that accommodating volunteers' preferences is more important than letting some staffing needs go unmet, and this preference is reflected in the model results. However, a relative benefit of the model in this respect is that by incorporating labor shortages (see Equation (8)), the decision maker is able to balance those shortages among shifts and centers.

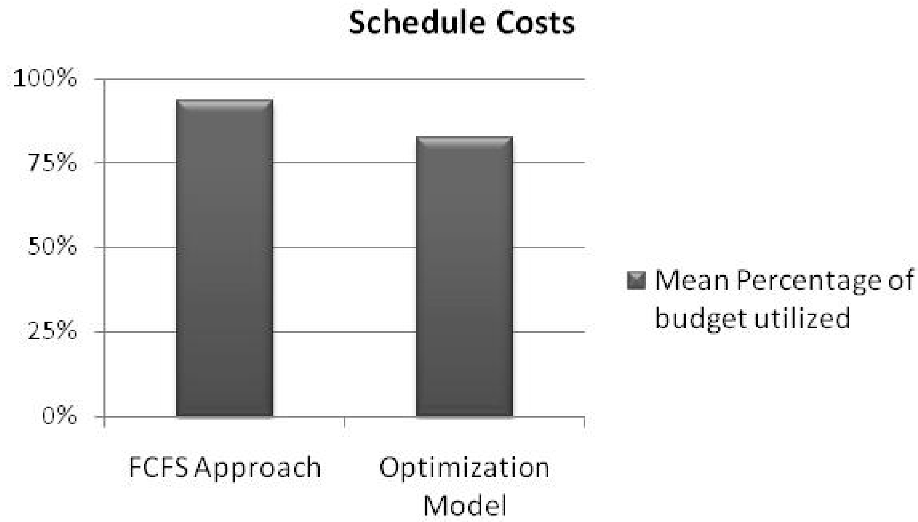

Figure 3.6: Mean results obtained with the two solution methods for the Cost objective

With respect to the third objective, total schedule costs, the percentage of utilized budget was reduced by an average of 12%. The hypothesis test for the Cost objective confirmed that the average results obtained with the optimization model were significantly lower than the ones obtained with the current approach at the 0.05 level of significance. It is relevant to note that even though this objective was the least important (and thus received the smallest weight in the formulation), the model was able optimize the payment of *per diems* and save resources by assigning, whenever possible, the same volunteer to the morning and afternoon shift. Given the limited budget of this organization, these savings are quite significant.

Conclusions and Lessons Learned

This paper discussed how the development of customized spreadsheet-based decision support models can help address some of the challenges and deficiencies faced by small development aid organizations. In particular, we showed how the model helped to better satisfy the volunteers' scheduling preferences, thus supporting long-term retention of the workforce. We also discussed how the proposed model helped to reduce the number of unfilled assignments and how it helped to decrease total scheduling costs. Other less tangible benefits mentioned by the organization included the ability to perform what-if analysis and the increased speed at which schedules could be generated.

Advances in spreadsheet modeling have made decision models accessible to different types of organizations, regardless of their size and budget. The use of spreadsheets in our study represented a low-cost and widely available alternative that made implementing the project significantly easier. Nonetheless, this approach provided enough flexibility and modeling power to develop a user friendly decision support tool.

As discussed above, business disciplines such as Finance have been successful at creating different instruments for poverty reduction in developing countries. We believe that small, focused applications of traditional OR/MS topics can also help in these environments by supporting and promoting more effective and efficient decision making. We hope that more applications of this kind will continue to emerge and that, in the future, the field of Micro-OR will continue to grow and thrive.

Appendix

Model

Decision Variables

x_{ijk} = 1 if volunteer *i* is assigned to shift *j* at center *k*, 0 otherwise

y_{jk} = Shortage of volunteers (number of persons) for shift *j* at center *k*

α_{ilk} = 1 if volunteer *i* is assigned to one or less shifts on day *l* at center *k*

β_{ilk} = 1 if volunteer *i* is assigned to both the morning and afternoon shifts on day *l* at center *k*

Data Sets

I = The set of all volunteers

A = The set of all afternoon shifts

J = The set of all shifts in the scheduling period

K = The set of all centers

L = The set of all days in the scheduling period

M = The set of all morning shifts

G = The set of all objectives

Parameters

a_{ijk} = 1 if volunteer *i* prefers not to be assigned to shift *j* at center *k*, 0 otherwise

c = *Per diem* allowance

e_{jk} = Number of volunteers required for shift *j* at center *k*

f = Available budget for the scheduling period

$\overline{v_i}$ = Maximum number of shifts to assign to volunteer *i* over the scheduling period

$\underline{v_i}$ = Minimum number of shifts to assign to volunteer *i* over the scheduling period

p_{jk} = Maximum allowed shortage of volunteers (number of persons) for shift *j* at center *k* over the scheduling period

u_i = Maximum allowed number of undesired assignments for volunteer *i* over scheduling period

w_g = Weight assigned to objective *g* over scheduling period

Model Formulation

$$\text{Min } w_1\left(\frac{\sum_{i\in I}\sum_{j\in J}\sum_{k\in K} a_{ijk}x_{ijk}}{\sum_{j\in J}\sum_{k\in K} e_{jk}}\right)+w_2\left(\frac{\sum_{j\in J}\sum_{k\in K} y_{jk}}{\sum_{j\in J}\sum_{k\in K} e_{jk}}\right)+w_3\left(\frac{c\left(\sum_{i\in I}\sum_{j\in J}\sum_{k\in K} x_{ijk}-\sum_{i\in I}\sum_{l\in L}\sum_{k\in K}\beta_{ilk}\right)}{f}\right) \tag{1}$$

where

$$w_1 > w_2 > w_3 \tag{2}$$

st

$$\sum_{i\in I} x_{ijk} + y_{jk} \geq e_{jk}, \quad j \in J, \text{ and } k \in K \tag{3}$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c x_{ijk} \leq f \tag{4}$$

$$x_{ijk} + x_{ij'k} = \alpha_{ilk} + 2\beta_{ilk} \quad i \in I,\ j \in M \cap L,\ j' \in A \cap L, l \in L, \text{ and } k \in K \tag{5}$$

$$\sum_{j\in J}\sum_{k\in K} a_{ijk}x_{ijk} \leq u_i, \quad i \in I \tag{6}$$

$$\underline{v_i} \leq \sum_{j\in J}\sum_{k\in K} x_{ijk} \leq \overline{v_i}, \quad i \in I \tag{7}$$

$$y_{jk} \le p_{jk}, \quad j \in J \text{ and } k \in K \tag{8}$$

$$x_{ijk} \in \{0,1\} \quad i \in I,\ j \in J, \text{ and } k \in K \tag{9}$$

$$y_{jk} \ge 0 \text{ and integer}, \quad j \in J, \text{ and } k \in K \tag{10}$$

$$\alpha_{ilk} \text{ and } \beta_{ilk} \in \{0,1\}, \quad i \in I, l \in L, \text{ and } k \in K \tag{11}$$

The objective function, (1), minimizes a weighted combination of the percentage of undesired assignments, the percentage of unfilled slots, and the percentage of the budget utilized. Equation (2) formalizes the relationship among the three objectives of the organization. As explained in previous sections, the percentage of undesired assignments must receive the highest weight, while the percentage of utilized budget should be assigned the lowest weight.

Constraint set (3) tries to ensure that an appropriate number of volunteers is assigned to each time shift at each center in order to satisfy the workload requirements determined by the organization. Constraint (4) makes certain that the actual schedule costs do not exceed the available budget, while constraint set (5) is used to manage more efficiently the payment of *per diems*.

Constraint set (6) places an upper limit on the number of undesired assignments for each volunteer over the scheduling period. Constraint set (7) ensures that volunteers receive an adequate number of assignments, while constraint set (8) balances labor shortages by placing an upper limit on the shortage of volunteers per shift over scheduling horizon. Finally, equations (9), (10) and (11) satisfy the different binary, non-negativity and integratility conditions for the decision variables.

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CHAPTER 4

AN OPTIMIZATION MODEL FOR HUMANITARIAN RELIEF VOLUNTEER MANAGEMENT

Chapter 4

An Optimization Model for Humanitarian Relief Volunteer Management

Abstract

One of the challenges of humanitarian organizations is that there exist limited decision technologies that fit their needs. It has also been pointed out that those organizations experience coordination difficulties with volunteers willing to help. The purpose of this paper is to help address those challenges through the development of a decision model to assist in the management of volunteers. While employee workforce management models have been the topic of extensive research over the past decades, no work has focused on the problem of managing humanitarian relief volunteers. In this paper, we discuss a series of principles from the field of volunteer management and develop a multicriteria optimization model to assist in the assignment of both individual volunteers and volunteer groups to tasks. We present illustrative examples and analyze two complementary solution methodologies that incorporate the decision maker's preferences and knowledge and allow him/her to trade-off conflicting objectives. Conclusions, limitations, and directions for future research are also discussed.

Keywords

Humanitarian Logistics, Multicriteria Decision Making, Fuzzy Logic, Optimization, Volunteer management

Introduction

It has been pointed out that humanitarian logistics is one of the most challenging logistics domains (Ratliff 2007). However, the field of humanitarian logistics has so far received limited attention by logistics academics (Kovács and Spens 2007). While the social sciences, economics and humanities literatures have developed a significant amount of work on humanitarian issues, this has not been the case for the decision sciences and operations management communities (Altay and Green 2006).

Different authors have identified a series of specific challenges faced by the field of humanitarian logistics (Thomas and Kopczak 2005; Kovács and Spens 2007). More specifically, Ratliff (2007) pointed out that there are limited information and decision technologies that clearly fit the needs of humanitarian relief organizations. The author also made the claim that one of the challenges of humanitarian logistics is that there are significant coordination difficulties with large numbers of volunteers all trying to help. We strongly believe that the development of decision support technologies could help address some of the deficiencies identified in the literature. For these reasons, our paper is aimed at developing a multicriteria optimization model to assist in the assignment of humanitarian relief volunteers to tasks. The contributions of this research are twofold: First, no previous work has focused on the problem of managing humanitarian relief volunteers. Second, there are no studies that have integrated efficiency analysis and fuzzy logic concepts in multicriteria decision making.

The remainder of this paper is organized as follows: A review of the literature related to volunteering and to workforce scheduling is followed by an overview of different defining characteristics of the field of volunteer management in a humanitarian context. Next, we outline the model developed for our study and present two complementary solution methodologies that can assist in the assignment of humanitarian relief volunteers. Finally, we conclude with a discussion of the implications and limitations of our research study, and outline future research directions.

Literature Review

The literature in the area of humanitarian logistics consists primarily of handbooks and general procedures developed by Non-Governmental Organizations that are aimed at structuring operational activities in humanitarian efforts. As pointed out by Beamon and Kotleba (2006), very little is available in terms of quantitative analysis of humanitarian relief logistics operations. For example, while employee workforce management models have been the topic of extensive research over the past decades, no work has focused on the problem of managing the assignment of humanitarian relief volunteers. Accordingly, our review of the literature focuses on previous volunteerism and workforce scheduling research.

Volunteer Management

Shin and Kleiner (2003) define a volunteer as any individual "who offers him/herself to a service without an expectation of monetary compensation." Volunteer management research has been an important topic in the social sciences. The different areas that have been researched include the motives for volunteering, i.e, the reasons why people volunteer (Cnaan and Goldberg-Glen 1991; Allison, Okun et al. 2002; Bussell and Forbes 2002). Opportunities for personal growth, recognition, achievement, and a desire to contribute to the community are some of the incentives for volunteering cited by past research. Another topic that has been studied in the past involves the demographic characteristics of volunteers, such as education and gender, and their relationship to present and future commitment levels (Lammers 1991; Van Vianen 2008).

The area of volunteer retention and the analysis of what practices encourage renewed volunteerism and why people continue to volunteer is also an important topic (Gidron 1984; Hager, Brudney et al. 2004). Some of the management practices that positively influence the retention of volunteers include recognition activities and matching volunteers to appropriate tasks. Gidron (1984), for example, cites task achievement and the quality of the work itself as some of the variables that could better predict volunteer retention.

Each of these areas of research reinforces the observation that volunteers play a vital role in the provision of assistance in humanitarian relief situations. The manner in which they do so, and the specific characteristics of their participation in relief efforts play an important role in the development of our model, as will be shown in later sections.

Labor Scheduling

Several articles have been published on labor scheduling as the topic has become gradually more important due to the prevalence of the services sector. However, volunteer management, in general, has not been discussed in the operations management literature.

Previous research can be categorized by type of model, by solution methodology and by application area. Relevant reviews of the state of the art include Alfares (2004) and Bechtold et al. (1991), among others. With respect to the solution methods and techniques, it has been noted that the literature is heavily skewed towards mathematical programming approaches (Ernst, Jiang et al. 2004). In addition, because of the size of some tour scheduling problems, different heuristic methods have been developed (See, for example, Goodale and Thompson (2004)).

The operations management literature includes several different application areas related to labor assignment problems. Since their inception, scheduling and staffing methods have been applied to areas ranging from airline crew staffing (Kohl and Karisch 2004) to nurse scheduling (Azaiez and Al Sharif 2005; Parr and Thompson 2007). However, a review of the literature related to labor scheduling research specifically focused on not-for-profit or volunteer contexts resulted in only two specific articles.

The first of these two articles, by Gordon and Erkut (2004), developed a model to schedule volunteers for an annual music festival. Although, as in our current research, the authors used an integer programming formulation to incorporate user preferences and constraints into the model, they did not explicitly consider the issue of labor shortages. Sampson (2006) developed an optimization model for labor assignments in the context of an international meeting. In addition, the author illustrated ways in which the volunteer management problems are different from typical paid workforce assignment problems.

In the disaster management field, Janiak and Kovalov (2006; 2008) studied scheduling problems where tasks need to be executed by human resources in areas contaminated with radio-active materials. In their model, the authors studied single worker problems with the objectives of minimizing maximum lateness or total weighted completion time. The idea of modeling volunteers' preferences, for example, was not considered. Another somewhat related article by Metters and Vargas (1999) also discusses issues related to nonprofit organizations from a quantitative decision modeling perspective. The authors extended yield management concepts to the nonprofit sector by developing a heuristic to assist in pricing decision making. Their technique was demonstrated at a nonprofit child care center. One of the key attributes of their model is the idea that profit maximization is not the most important goal.

Overall, while employee scheduling has been the topic of extensive research over the past decades in the business literature, no previous work has focused on the problem of optimizing the assignment of humanitarian relief volunteers.

Characterization of a Humanitarian Volunteer Management Model

This section provides a brief overview of the different defining characteristics of volunteer management in humanitarian organizations. We first explore what characteristics make a humanitarian decision model different from a traditional business model, and then analyze some additional ideas from the field of volunteer management that played an important role in the development of our model.

Differences between traditional business models and humanitarian models

A key difference between traditional business models and humanitarian models is that of the objective function. Rather than maximizing revenues, the objective function for a humanitarian organization should support its social mission (i.e., to save lives and to alleviate suffering).

Another important difference between traditional business models and humanitarian models is related to the skills of the labor force. Traditional business models assume that the available labor force has the required skills to complete a task. In the case of humanitarian organizations, one must take into consideration that some volunteers may not have the required skill levels to complete certain tasks. For that reason, humanitarian organizations must avoid inefficiencies in the management of skilled volunteers. In the aftermath of the 2004 tsunami, for example, numerous skilled volunteers came together to work for the common good. Those individuals came from all over the world but it was pointed out that the skills of many of the volunteers were not used to the maximum: “A large number of volunteers, became disenchanted because of the lack of organization (…). Some highly-skilled volunteers were asked to perform repetitive jobs” (Anonymous 2005).

In addition, traditional labor assignment research typically assumes that a sufficient labor pool is available. On the other hand, humanitarian organizations rely heavily on the use of volunteers to implement their humanitarian efforts. Those organizations typically depend on a large number of volunteer workers with limited time availabilities to accomplish their missions. The future will be even more challenging: it has been claimed that even though the amount of work required in the voluntary sector is growing, the number of available volunteers is not increasing at a comparable rate (Bussell and Forbes 2002). Therefore, it is important for humanitarian and other non-profit organizations to manage efficiently the available volunteer workforce in order to successfully recruit and retain their volunteer bases.

The table below, adapted from Sampson (2006), discusses how humanitarian volunteer management problems differ from paid labor problems with respect to various decision model attributes. Most of those distinctions were confirmed by Sampson with empirical data and determine a mathematical formulation that is different from traditional formulations for business problems.

Model Attribute	Paid Workforce	Humanitarian Volunteer Workforce
Key Objective	Maximize profits by minimizing labor costs	Maximize task completion by minimizing shortages
Key constraint	Demand level	Volunteer labor size
Labor pool size constraint	Sufficient/unconstrained	Size of committed labor
Labor costs	Non-zero	Low yet still non-trivial
Labor preferences	Employees' shift preferences may be considered	Volunteers' time and task preferences must be considered
Shortages	Not an issue	Shortages need to be balanced among shifts and tasks

Table 4.1: Comparison of paid labor and humanitarian volunteer labor scheduling models

A model for humanitarian organizations must ensure that the resources available be used efficiently. In addition, such a model must try to make sure that enough volunteers are available at all times while taking into account individual preferences in such a way that volunteers are treated fairly. The discussion above reveals that the modeling of the volunteer scheduling problems requires the consideration of multiple objectives. Specifically, the volunteer management problem needs to be formulated so as to select a configuration of schedules that balances the trade-off between available resources and volunteer preferences.

Additional considerations from the field of volunteer management

Any such model must also take into consideration other hypotheses from the volunteer management literature that were empirically tested and verified by Sampson (2006). Those considerations are discussed below.

- The level of future committed labor (CL) is directly related to the current assignment of tasks. Consequently, a volunteer management model should take into consideration and satisfy as much as possible the volunteers' preferences for task and time block assignments.
- The use of volunteer labor up to level of CL will maintain/increase future CL. On the other hand, use of volunteer labor beyond CL will decrease future CL. In this respect, a volunteer management model should avoid over utilization of volunteer labor.
- Utilized volunteer labor will be more likely to volunteer in the future than unutilized volunteer labor. In this sense, a model should provide solutions that avoid non-utilization or under utilization of volunteer labor, whenever possible.
- Task demands in excess of current CL will result in shortage costs. This postulate simply indicates that a volunteer management decision model should maximize task completion making use of volunteer labor as much as possible in order to avoid shortages.

The characteristics discussed above imply the need for a mathematical formulation that is intrinsically different from that of traditional business decision models.

Proposed Model

Our volunteer management model is designed to assist in the assignment of both individual volunteers and volunteer groups (e.g. church groups) to tasks. The model is presented as a bicriteria integer programming model with binary (0,1) and general integer variables. The two objectives are structured as follows: In the first objective, we are interested in minimizing task shortages. The first objective function thus minimizes total shortage costs. Shortage costs represent a penalty and occur when a certain time block remains unassigned. In addition, the model takes into consideration individual time and task preferences (e.g., a request to have a certain day or time block off) so that volunteers are treated fairly. For that purpose, the second objective function minimizes the number of undesired assignments. Taken together, these two objectives contribute towards the overall mission of saving lives and alleviating suffering while using resources more efficiently and effectively.

Data Elements

The reader should note that volunteer data can be available from existing computerized Disaster Management software systems. Such systems are available to help humanitarian organizations structure the data they collect and can also allow organizations to use different types of decision models. The Sahana Volunteer Management Project developed by the Humanitarian FOSS Project at Trinity College, for example, is a free and open source humanitarian software module for Sahana that allows the users to coordinate the contact information, skills, assignments and availability of volunteers and responders (TheHumanitarianFOSSProject@Trinity 2008). Other types of data that should be stored and retrieved, in support of the model, include more specific preferences of volunteers (in terms of tasks and time blocks). The model data elements are presented below.

Decision Variables

x_{ijk} = 1 if volunteer or group *i* is assigned to time block *j* of task *k*, 0 otherwise

y_{jk} = Integer variable that represents the shortage of volunteers (number of persons) for time block *j* of task *k*

The solution to the volunteer management problem is, thus, the assignment of different volunteers (individual volunteers or volunteer groups) to a time block of each required task. We represent this solution by a set of binary variables that assume a value of 1 if an individual volunteer or a volunteer group is assigned to a certain time block to perform a determined task, and a value of 0 otherwise. A second set of integer variables represents the shortage of volunteers (in terms of number of persons) for each specific time block of a task.

Data Sets

V = The set of all volunteers (individuals or groups)

T = The set of all time blocks in the scheduling period

K = The set of all tasks

Parameters

n_i = The total size of volunteer group *i* (n_i = 1 for individuals, 2 or greater for groups)

e_{jk} = The total number of volunteers (number of persons) required for time block *j* of activity *k*

d_{jk} = Task shortage cost for time block *j* of task *k*

$\overline{v}_i$ = Maximum number of time blocks to assign to volunteer or group i

$\underline{v}_i$ = Minimum number of time blocks to assign to volunteer or group i

u_i = Maximum number of undesired time blocks assigned to volunteer or group i over scheduling period

w_i = Maximum number of undesired tasks assigned to volunteer or group i over scheduling period

p_{jk} = Maximum shortage of volunteers (number of persons) for time block j of task k

a_{ij} = 1 if volunteer or group i prefers not to be assigned to time block j, 0 otherwise

b_{ik} = 1 if volunteer or group i prefers not to be assigned to task k, 0 otherwise

f = Available budget for the scheduling period

c_{jk} = Cost of utilizing a volunteer for time block j of task k

z = Total length of the scheduling period

Model Formulation

The general model formulation is presented as follows:

$$\text{Min} \sum_{j \in T} \sum_{k \in K} d_{jk} y_{jk} \qquad (1)$$

$$\text{Min} \sum_{i \in V} \sum_{j \in T} a_{ij} n_i x_{ijk} + \sum_{i \in V} \sum_{k \in K} b_{ik} n_i x_{ijk} \qquad (2)$$

st

$$\sum_{i \in V} n_i x_{ijk} + y_{jk} \geq e_{jk}, \quad j \in T, \text{ and } k \in K \qquad (3)$$

$$\sum_{i\in V}\sum_{j\in T}\sum_{k\in K} c_{jk} n_i x_{ijk} \le f \tag{4}$$

$$\underline{v_i} \le \sum_{i\in V} x_{ijk} \le \overline{v_i}, \quad j \in T, k \in K \tag{5}$$

$$\sum_{j\in T} a_{ij} x_{ijk} \le u_i, \quad i \in V \text{ and } k \in K \tag{6}$$

$$\sum_{k\in K} b_{ik} x_{ijk} \le w_i, \quad i \in V \text{ and } j \in T \tag{7}$$

$$y_{jk} \le p_{jk} \tag{8}$$

$$x_{ijk} \in \{0,1\}, \quad i \in V, j \in T, \text{ and } k \in K \tag{9}$$

$$y_{jk} \ge 0 \text{ and integer}, \quad j \in T, \text{ and } k \in K \tag{10}$$

The first objective function, (1), minimizes total shortage costs. Total shortage costs represent a way to model the idea discussed in the previous section that task demands in excess of current CL will result in task shortages. The model will thus try to make use of volunteer labor as much as possible in order to satisfy task demands. In this way, shortage costs are related to resource maximization; they can be treated as a penalty function so that unfilled schedules are considered less optimal than those which are filled.

Objective function (2) minimizes the number of undesired task and time block assignments. Undesired assignments are calculated by having each volunteer or group specify which time-blocks and which tasks they would rather be assigned, and then by minimizing the number of time blocks and tasks they are assigned to that were not requested in the first place.

Constraint set (3) tries to ensure that an appropriate number of persons is assigned to each time block and task in order to satisfy the workload requirements determined by the decision maker. The right hand side of constraint set (3) represents the set of desired service levels.

Constraint (4) makes certain that actual schedule costs do not exceed the available budget level. Constraint set (5) ensures that volunteers are assigned to an adequate number of time blocks. As discussed in previous sections, a volunteer management model should provide solutions that help decision makers avoid both overutilization and non-utilization of volunteer labor. For example, based on the information provided by a volunteer the decision maker might determine that the volunteer should be assigned between 3 and 7 time blocks over the scheduling horizon. The underlying premise is that volunteers should be treated fairly and not be over worked.

Constraint sets (6) and (7) place upper limits on the number of undesired assignments with respect to both time blocks and tasks assigned to each volunteer or group over the scheduling period. In this sense, since previous research has found that volunteers that are treated fairly are more likely to volunteer in the future, the model should satisfy volunteer preferences for assignments as much as possible. Constraint set (8) places an upper limit on the shortage of volunteers per task over the scheduling horizon. As mentioned in the previous section, task shortages should be balanced among tasks in a humanitarian volunteer management model. The decision maker can thus use this set of constraints to balance the use of volunteer labor among different tasks. Finally, constraint sets (9) and (10) enforce non-negativity, integrality and binary conditions.

The reader should note that the constraints presented above could be modified (e.g., an organization might want to use different time block lengths) or additional constraints could be added in order to incorporate more specific organizational policies (e.g., policies that take into consideration the seniority of volunteers). The size of a typical problem is fairly large and will usually contain over a thousand binary and integer variables, as well as several thousand constraints. The inclusion of volunteer groups, however, can help reduce the size of the decision problem.

We now solve our decision problem using two complementary solution methodologies that can assist in the assignment of humanitarian relief volunteers. The first is a basic efficient frontier approach that allows the decision maker to trade-off conflicting objectives. The second approach uses a fuzzy formulation that incorporates the decision maker's preferences and knowledge to further support decision making in volunteer management settings.

Solution Methodology I: Efficient Frontier Approach

A traditional method for solving bicriteria problems is the efficient frontier method (Winston 2004). In this approach, a set of optimal (i.e., efficient) solutions must be generated. In our model, we achieve that goal by first minimizing objective function (1) (At this point, we ignore objective function (2)). We then express the resulting solution ($z^{shortage}$) as a function of the parameter β, and set the solution as a constraint. As a result, we have a new constraint in our model:

$$\sum_{j \in T} \sum_{k \in K} d_{jk} y_{jk} \leq \beta z^{shortage} \qquad (11)$$

Next, we proceed to solve the model minimizing the number of undesired assignments, i.e., objective function (2). Objective function (2) is now expressed as:

$$\text{Min } z^{undesired} = \sum_{i \in V} \sum_{j \in T} a_{ij} n_i x_{ijk} + \sum_{i \in V} \sum_{k \in K} b_{ik} n_i x_{ijk} \qquad (12)$$

Note that from (11), the resulting solution ($z^{undesired}$) will now depend on the value of β. In order to develop the efficient frontier (i.e. a trade-off curve between the two conflicting objectives), we now must repeatedly solve the modified model for different β values greater than 1. Next, we simply need to plot the different combinations of $z^{undesired}$ and $z^{shortage}$ values.

Finally, the decision maker will:

1. inspect the tradeoff curve,
2. select the point in the curve that, based on his experience and preferences, most appropriately balances the two conflicting objectives, and
3. implement the corresponding schedule.

Illustrative Example and Results

We now present computational results from randomly generated instances. In our example, we have several hundred volunteers (including both individuals and groups) that need to be assigned to a series of tasks over the course of one week. The software used to solve the instances was the Risk Solver Platform from Frontline Systems, Inc. The resulting tradeoff curve is presented below.

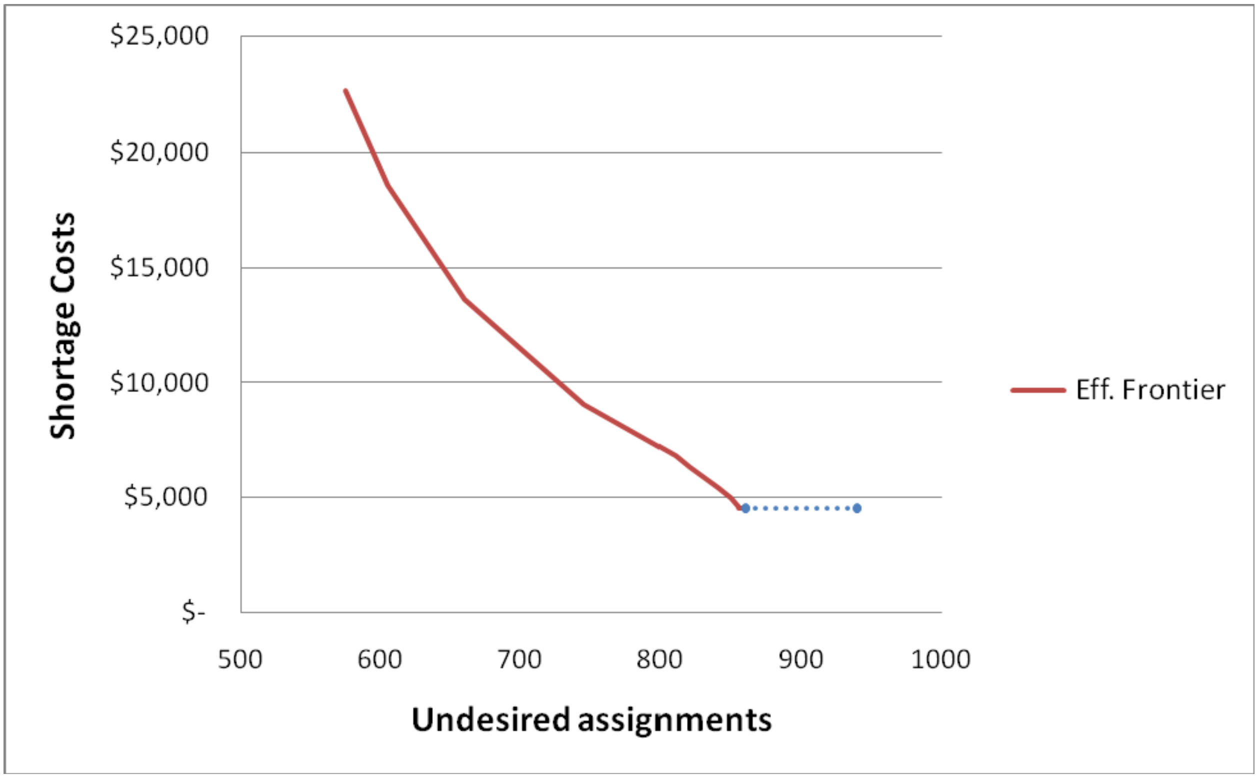

Figure 4.1: Efficient Frontier Results

The solution methodology first minimizes shortage costs in order to get as much coverage as possible and then focuses on minimizing the number of undesired assignments. As shown in the figure above, minimizing the number of undesired assignments without incurring any additional shortage costs (i.e., $\beta = 1$) results in an initial reduction of that number. Then, as β is subsequently increased, shortage costs start to increase while the number of undesired assignments starts to go down.

As implied above, there are two extreme scenarios. The first one is concerned with guaranteeing coverage and requires minimizing shortage costs as much as possible ($\beta = 1$) given the labor that is available. This solution would be appropriate in a disaster response or recovery situation when the immediate/time-critical need to offer assistance for survivors will outweigh most other considerations (it would be safe to assume that in such situations most volunteers would be less worried about the quality of their schedules and would be more focused on working as hard as possible, as soon as possible). The second scenario, on the other end of the curve, might be more appropriate in the mitigation or post-crisis recovery stages where the long-run completion of tasks is ultimately the goal, and therefore in the short-term it would not be a significant issue to let some staffing needs go unmet in order to have volunteers come back in future periods. That is, a decision maker could decide to have some shifts uncovered in order to improve volunteer morale.

Ultimately, based on the context and the types of needs, the decision maker would use his/her experience and expertise to select a point in the curve and implement the corresponding schedule.

Solution Methodology II: Fuzzy Logic Approach

The previous section explained how the decision maker exercises his/her preferences in the efficient frontier approach. In this approach, the decision maker's preferences about the relative importance of each objective are only exercised *post-hoc* when he or she trades-off objective values on the efficient frontier. In this section, we describe how fuzzy logic can be used in our model to incorporate the decision maker's preferences and knowledge *a priori* to further support decision making in volunteer management settings.

Fuzzy Logic and Fuzzy Membership Functions

Fuzzy logic is a form of mathematics that can be used to represent imprecision in a mathematical model's variables. Many decision-making situations such as disaster relief scenarios are too complex to be represented using precise quantitative information. Nevertheless, a decision maker may be able to use knowledge that is imprecise in order to arrive at a solution. In this sense, fuzzy logic resembles human reasoning in its use of approximate information to model decisions.

In the volunteer management model, the different objectives for potential schedules can be defined as fuzzy sets. Each fuzzy set can thus be represented by a function that relates each value to a grade of membership. Such a function is known as a membership function. Membership functions are built based on subjective knowledge and are, therefore, dependent on the decision maker and the problem situation. For example, the total shortage costs objective can be defined as a fuzzy set called “Acceptable Shortage Costs” which relates the schedule’s shortages to a grade of membership in the fuzzy set. An example of a membership function for “Acceptable Shortage Costs” is presented in the figure below.

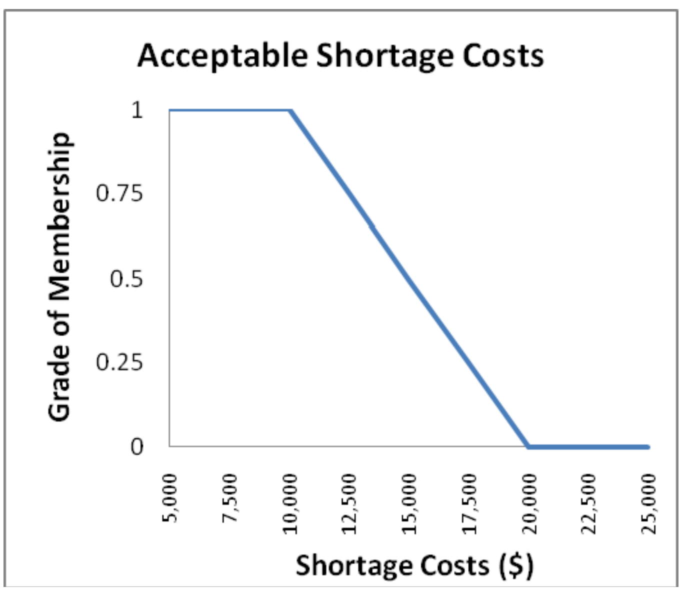

Figure 4.2: “Acceptable Shortage Costs” membership function

In the example above, a schedule that results in shortages equivalent to $17,500 is given a grade of membership of 0.25 in the fuzzy set. The higher the total shortage costs for a particular schedule, the lower the grade of membership, and vice versa. As a result, the objective no longer has single crisp value but instead is reflected as a value in the membership function. Based on the principles of fuzzy logic, we seek to maximize the value of the membership function, which, in our model, would result in minimizing the total shortage costs.

In this sense, fuzzy logic provides a formalized framework for dealing with the imprecision intrinsic to our decision problem. Since knowledge can be represented in a more natural way by using fuzzy sets, our decision situations can be simplified. The use of fuzzy logic allows our model to consider multiple objectives without the need for assigning any weights or selecting any ordered rankings for objectives.

Objectives as Membership Functions

In this approach, we use the decision maker's preferences and knowledge to build fuzzy membership functions and then use those functions to direct the decision maker to a point in the efficient frontier and further assist him/her in the decision making process.

In order to accomplish our research objective, we adapt our original model formulation and transform it into a fuzzy multiple criteria linear optimization problem. In essence, we replace the two crisp objectives with two fuzzy membership functions.

The membership function for "Acceptable Shortage Costs" presented in Figure 4.2 above reflects the decision-maker's preferences or desired levels of shortages as an objective. For the membership function in Figure 4.2, total shortages costs of $17,500 or more result in low grades of “acceptable shortage costs”, while total equivalent to $15,000 or less result in higher grades of membership.

We can construct a membership function for the second objective, i.e., the number of undesired assignments. This membership function is presented in the figure below.

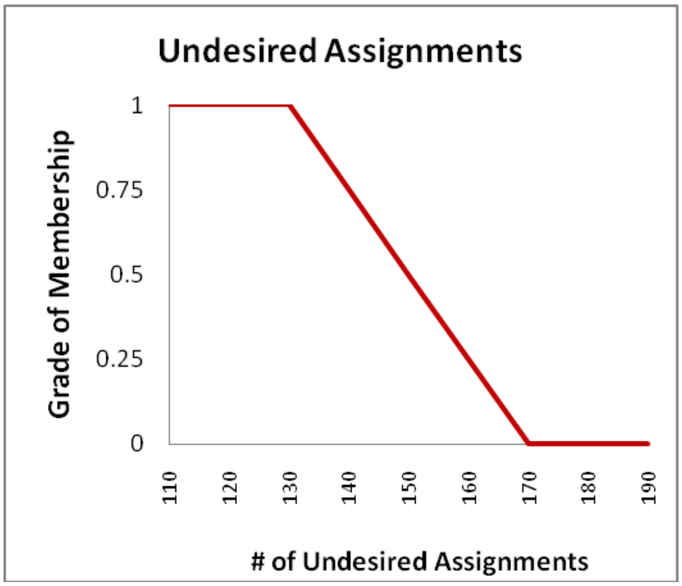

Figure 4.3: “Number of Undesired Assignments” membership function

In this case, a total of 170 undesired assignments or more would result in a degree of membership equal to zero while a total of 160 or less undesired assignments would result in higher grades of membership. Thus, the problem of incommensurate multiple objectives is addressed by utilizing a fuzzy membership function for each objective.

As shown in the figures above, the membership functions are defined by two parameters: a lower quantity, denoted by l, and an upper quantity, denoted by u (e.g., 130 and 170, respectively, in the figure above). Therefore, each objective’s membership function can be formally described by the formula below.

$$\mu_{(o,l,u)} = \begin{cases} 0, & o < l \\ \dfrac{o-l}{u-l}, & l \le o \le u \\ 1, & o > u \end{cases} \tag{13}$$

Finally, an “overall” objective function is created in order to solve the volunteer labor scheduling problem using the fuzzy solution approach. In this case, the objective function seeks to maximize the sum of the individual grades of membership for the fuzzy sets. Our new objective function is thus expressed as:

$$\text{Max } z^{fuzzy} = \mu^{shortage} + \mu^{undesired} \tag{14}$$

The following example illustrates how the fuzzy approach works. Consider the two alternative schedules presented in the table below.

	Schedule A	**Schedule B**
Shortage Costs	\$20,000	\$17,500
Undesired Assignments	130	160

Table 4.2: Two sample schedules

Using the membership functions presented in Figures 4.2 and 4.3 we can determine the objective function value for each of the two schedules. Schedule A results in an objective function value of 1 + 0 = 1, while Schedule B results in an objective value of 0.25 + 0.25 = 0.5.

Since the objective function is the sum of the degrees of membership for each objective, Schedule A would be selected as it results in a higher objective function value.

Illustrative Example and Results

We next proceed to solve our volunteer labor scheduling problem using the fuzzy approach. In order to illustrate the value of the fuzzy approach we developed 3 alternative sets of membership functions that represent different relief scenarios.

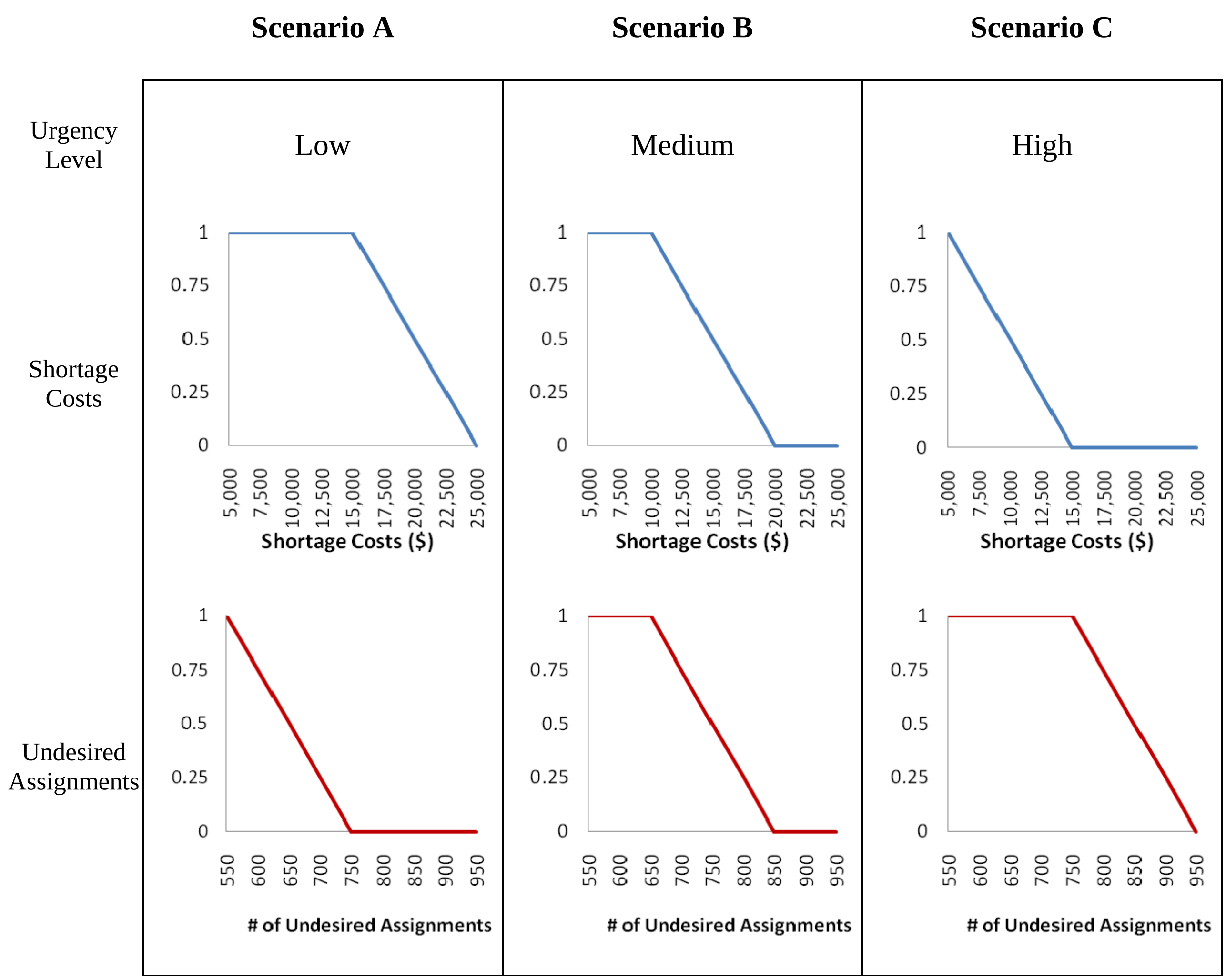

Table 4.3: Membership functions related to three alternative relief scenarios

In the table above, Scenario A represents a low urgency scenario. In this case, the decision maker seeks to minimize the number of undesired assignments as much as possible and is willing to leave a larger number of shifts uncovered. On the other hand, Scenario C represents a high urgency situation where the decision maker is interested in keeping shortages to a minimum and, therefore, is willing to allow a larger number of undesired assignments. The third set of membership functions represents a scenario contained within the two extreme situations described above.

The results of our two objective fuzzy optimization model for each of the three scenarios described above (along with the efficient frontier results obtained in the previous section) are shown in Figure 4.4.

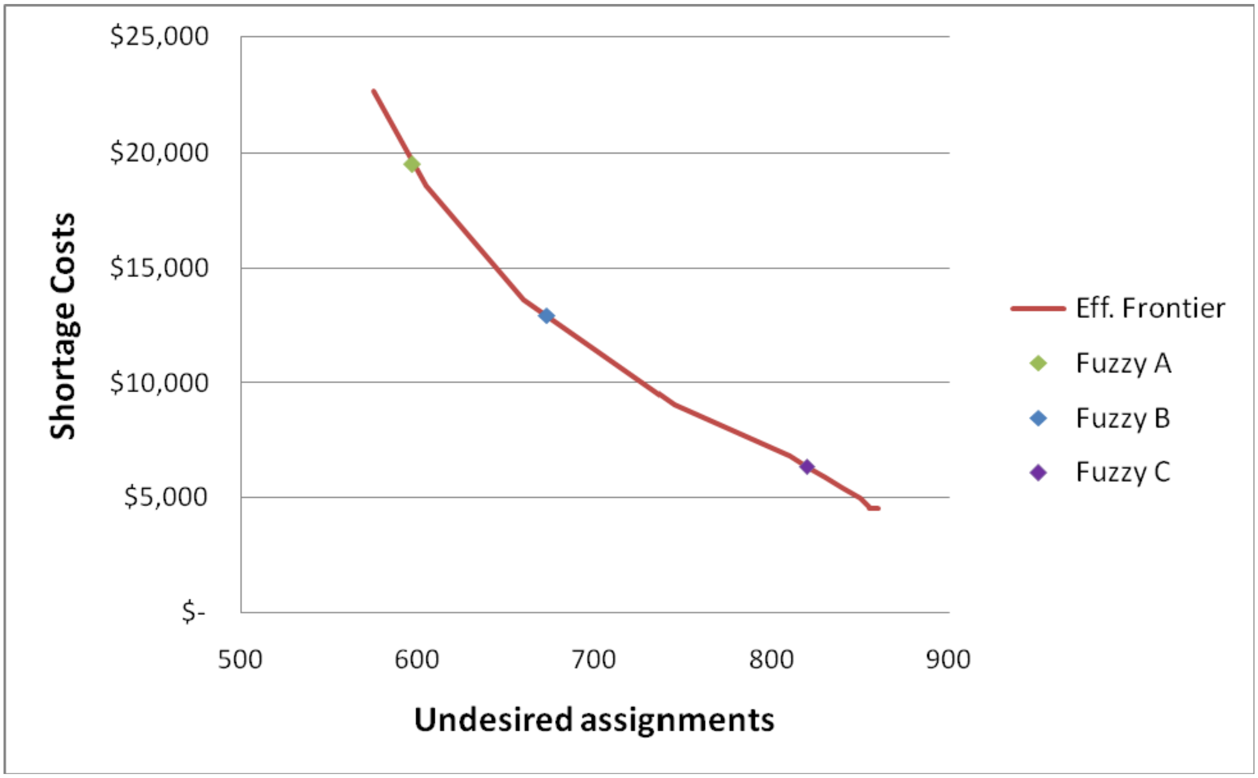

Figure 4.4: Plot of fuzzy model results vs. efficient frontier results

As shown above, the results of the two objective fuzzy model correspond to the efficient frontier line obtained with the solution approach used in the previous section.

Moreover, the fuzzy model solution using the membership functions which reflect a low urgency level scenario (Fuzzy A) maps to points located on the fewer undesired assignments/higher shortages end of the efficient frontier. On the other hand, the fuzzy model solution using the membership functions which reflect the decision maker's preference for keeping shortages to a minimum (Fuzzy C) maps to points located on the fewer shortages end of the efficient frontier.

Overall, our results indicate that a fuzzy multiple objective solution approach provides solutions that are as good as the solutions obtained using the efficient frontier method since the solutions of our two objective fuzzy model overlap with the optimal efficient frontier solutions (assuming the same data set is used in each approach). The example illustrates how we can use the decision maker's preferences and knowledge to build fuzzy membership functions and then use this information to direct the decision maker to a specific section of the efficient frontier. The results thus validate the fuzzy approach and suggest its use as a guidance tool for decision makers that can be used in conjunction with the efficient frontier method to further support the decision making process.

Conclusions and Future Research

The purpose of this paper was to help address some of the challenges faced by humanitarian organizations through the development of a volunteer management model. For that purpose, a multicriteria optimization model to assist in the assignment of volunteers to tasks was developed. In addition, we reviewed a series of important principles from the field of volunteer management and discussed how a volunteer labor force model differed from a traditional business model. We also presented two complementary solution methodologies and an analysis of their performance was undertaken. In this sense, we showed how our model can be used to assist in the management of volunteers and help the decision maker deal with conflicting objectives by providing computer-aided decision support.

The multicriteria nature of volunteer management is extremely relevant. On the one hand, humanitarian organizations need to manage volunteers wisely so that they become a renewable resource. On the other hand, these organizations need to keep shortages to a minimum (understanding that additional volunteers may not be available to take up the slack) in order to increase the effectiveness of their efforts. Therefore, even though the efficient use of resources is important, it may not be enough in the event of a humanitarian crisis. There is thus a clear need to balance conflicting objectives. The decision maker will ultimately need to solve this issue based on his or her experience and preferences. An important characteristic of our solution approach is its support for the decision maker to easily consider the impact of tradeoffs between the two conflicting objectives in humanitarian relief, or crisis management scenarios.

The multiple criteria solution methodology presented in our paper has some limitations. One major limitation of the two-dimensional efficient frontier approach discussed in our paper is the impossibility of reasonably including more than two objectives. Ongoing research is studying the use of fuzzy logic to overcome this limitation. Using the fuzzy multiple objective approach permits the inclusion of as many objectives as a decision requires. Essentially, our model could be extended to any number of objectives by incorporating additional fuzzy membership functions for each objective. The objective function would then be set to maximize the sum of all the individual grades of membership for the different fuzzy sets, as in (14). For example, a third objective representing total schedule costs could be added to the model formulation, as shown in the figure below.

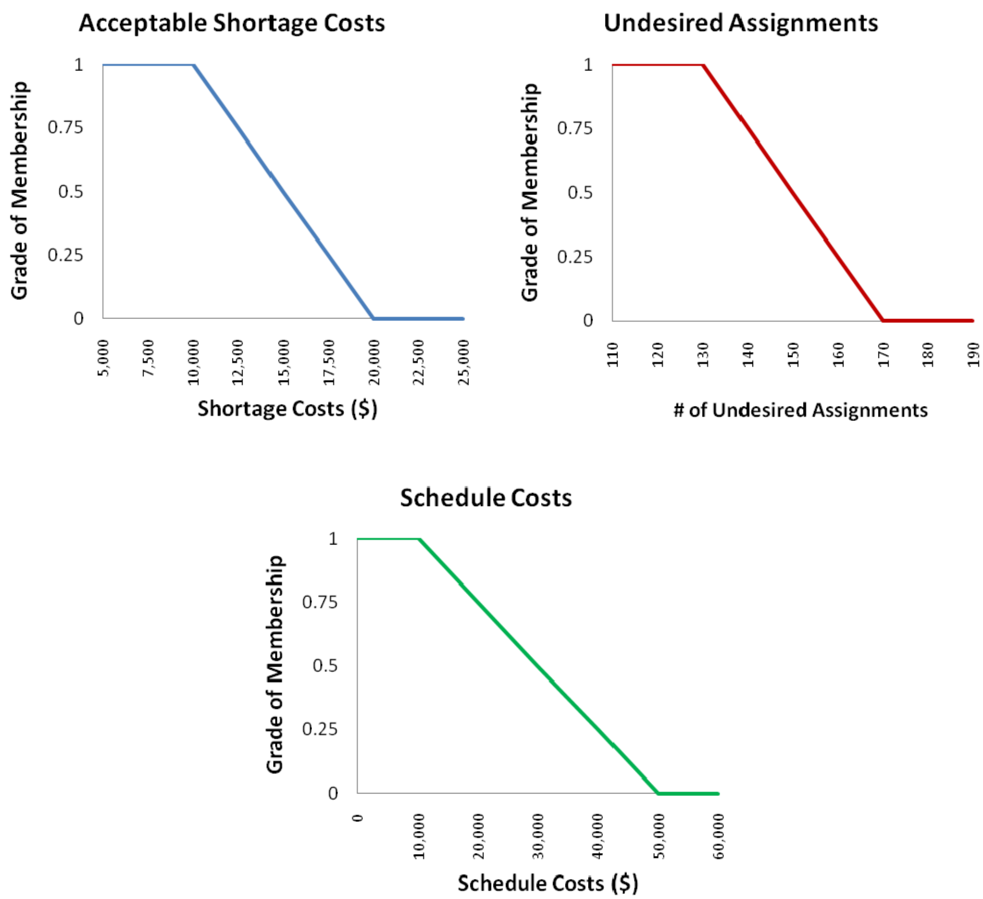

Figure 4.5: A fuzzy three-objective model

From a modeling perspective, the ability to include more than two objectives is significant because it overcomes a major limitation of the two-dimensional efficient frontier approach. Exploring alternative solution methodologies would further strengthen the applicability and importance of this work in the context of providing computer-aided decision support.

With respect to the fuzzy logic approach, one should note all the membership functions that were used are linear. These membership functions are used in our model because of their simplicity and efficiency with respect to computability. It should be noted that the shape of the membership functions can also be non-linear, etc. Ultimately, the model should utilize the shape that best reflects the decision maker's objectives. Further research with respect to decision makers' preferences would provide more accurate representations of the nature and form (linear, nonlinear, or discrete) of those membership functions. In this sense, the effects of nonlinear and discrete shaped membership functions on the mapping of solutions merits further examination.

A potential path for future research includes analyzing alternative scheduling decisions with different mixes of individual volunteers and volunteer groups. In order to analytically quantify the increase in dissatisfaction for a certain individual/group we would need to add an additional parameter:

γ_n = Dissatisfaction factor for volunteer groups of size *n*.

Consequently, our Undesired Assignments objective function would need to be modified as follows:

$$\text{Min} \sum_{i \in V} \sum_{j \in T} a_{ij} \gamma_n n_i x_{ijk} + \sum_{i \in V} \sum_{k \in K} b_{ik} \gamma_n n_i x_{ijk} \qquad (15)$$

As mentioned in previous sections, the inclusion of volunteer groups can help reduce the size of the decision problem and, from a modeling perspective, simplify the solution process. From a real life perspective, the inclusion of volunteer groups can also help simplify the actual implementation and management of the schedule. For example, instead of dealing with five individual volunteers, an organization might prefer to assign one group of five volunteers to different time blocks and then have the group allocate their (potentially) larger membership to these time blocks accordingly. Including a dissatisfaction factor in the model would thus allow the decision maker to prioritize the scheduling of volunteer groups and analyze the relative importance of satisfying volunteer groups of different sizes.

Future research may also look at formulating a combined planning and scheduling model. Workforce planning deals with decisions that are more strategic in nature. In our context, it would involve determining the volunteer workforce levels required by a humanitarian organization in order to achieve a certain goal. Past studies that integrate both planning and scheduling decisions include Venkataraman and Brusco (1996) and Thompson (1995), among others. A volunteer workforce planning model would help determine how many volunteers should be recruited, and then this information could be fed into the scheduling model.

The volunteer management distinctions and the model formulation are quite general, and can be easily applied to other humanitarian aid contexts. For example, ongoing research is examining the related problem of assigning volunteers for youth counseling in low income neighborhoods of a South American developing country. Future research might also look at ways of adapting the model formulation to meet other humanitarian scenarios. Finally, even though our research is unique in terms of combining efficiency analysis and fuzzy logic to solve volunteer labor scheduling problems, it has broader implications not only for other types of scheduling problems commonly found in service applications but also for all other types of multiple criteria decision making problems.

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CHAPTER 5

A TWO-STAGE DECISION MODEL FOR PROCUREMENT IN HUMANITARIAN RELIEF SUPPLY CHAINS

Chapter Five

A Two-Stage Decision Model for Procurement in Humanitarian Relief Supply Chains

Abstract

Humanitarian relief and aid organizations all over the world implement a wide variety of efforts aimed at recovering from disasters, reducing poverty and promoting human rights. Despite the prevalence of procurement expenditures in humanitarian efforts, procurement in humanitarian contexts is a topic that has only been discussed in a qualitative manner in the literature. The purpose of this work is to help close this gap through the development of a decision model for the procurement of goods in humanitarian efforts. In our paper, we introduce a two stage decision model with recourse for procurement in humanitarian relief supply chains and present an illustrative example. Conclusions, limitations, and directions for future research are also discussed.

Keywords

Humanitarian Logistics, Procurement, Decision Modeling, Optimization, Stochastic Programming

Introduction

Humanitarian relief and aid organizations all over the world implement a wide variety of efforts aimed at recovering from disasters, reducing poverty and promoting human rights. In the process, they procure an estimated US$ 50 billion worth of goods and services from local and international suppliers, with the procurement of goods representing around 60% of all procurement expenditures (Taupiac 2001). The volume of goods and services procured by these organizations has been steadily increasing. In this sense, Taupiac (2001) found that the volume of goods and services procured by the United Nations between 1996 and 2000 increased by around 40%.

Overall, humanitarian-focused procurement activities can be divided into two categories: procurement for development aid, and procurement for humanitarian relief. Even though the two categories have some characteristics in common, there are some important differences. The first category represents development aid efforts aimed at long term social and economic development. Goods and services for development can be delivered following normal lead times which, in turn, allows for evaluation and bidding procedures that resemble the functioning of commercial supply chains. In the case of humanitarian relief procurement, the primary emphasis is on speed and availability in order to save lives. Even though items procured for humanitarian relief operations tend to be relatively simple in design, that does not mean their cost is trivial. As a matter of fact, relief items tend to be fairly expensive since quick delivery is the main concern (Taupiac 2001). Humanitarian relief procurement will be the specific focus of this paper.

The procurement process plays a key role in humanitarian efforts by meeting requests for relief supplies. As shown in Figure 5.1 below (based on data presented by Blecken and Hellingrath (2008)), it is estimated that procurement activities account for 65% of expenditures in disaster relief logistics.

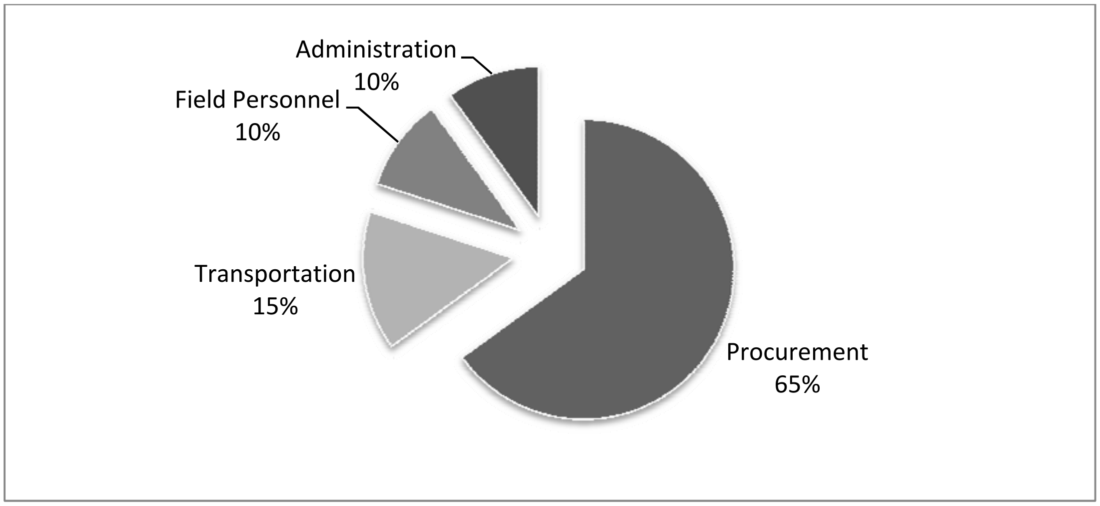

Figure 5.1: Expenditures in Humanitarian Relief Logistics

However, despite the prevalence of procurement expenditures in humanitarian efforts, the existing humanitarian logistics literature has focused primarily on facility location, inventory management, and transportation processes. To date, procurement in humanitarian relief is a topic that has only been discussed in a qualitative manner in the literature and has not been based upon scientific methodology. For this reason, we will develop a decision model to improve the procurement of goods in humanitarian operations.

The organization of this paper is as follows. We begin with a discussion of the existing research within the areas of humanitarian relief logistics and stochastic decision modeling for disaster relief. This is followed by a focused look at procurement activities in the context of humanitarian relief efforts, where we establish the need for adjusting the decision-making process under conditions of extreme uncertainty. We then introduce a two-stage stochastic programming model for the humanitarian procurement process and present an illustrative example. Conclusions, limitations, and directions for future research are also discussed.

Literature Review

The humanitarian relief procurement problem falls in the area of humanitarian supply chain management, which has been defined by Thomas and Kopczak (2005) as the process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from the point of origin to the point of consumption for the purpose of improving social welfare and alleviating the situation of vulnerable people. The humanitarian logistics function encompasses a wide range of activities, which include disaster preparedness and planning, procurement, transportation, warehousing, tracking and tracing, and customs clearance (Thomas and Kopczak 2005). A discussion of the existing research within the field of humanitarian relief logistics is presented next.

Humanitarian Logistics

Despite the important role played by humanitarian logistics in aiding people made vulnerable by natural disasters and crises, the literature in this area is fairly limited (Moody 2001; van Wassenhove 2006). In general, most papers have simply provided qualitative insights into the problem.

In the line of qualitative research, Long (1997), for example, discussed the basic characteristics of disaster relief logistics. Alexander (2006) performed an analysis of organizational and logistical processes in disaster relief, while Van Wassenhove (2006) provided an overview of the similarities and differences between business and humanitarian logistics, and discussed the idea of cross learning opportunities between the humanitarian and the private sectors.

The literature in the area of humanitarian relief logistics also contains a wide array of handbooks and general procedures developed by non-governmental organizations. The Fritz Institute, for example, has published different reports that survey the performance of humanitarian logistics efforts and provide qualitative insights related to the relevance of logistics in disaster relief (Thomas and Kopczak 2005; Thomas and Ramalingam 2005; Bliss and Larsen 2006; Bliss and Campbell 2008).

From a supply chain decision modeling perspective, the existing literature can be classified into three main categories: inventory management, facility location, and transportation applications. The inventory management literature in the context of humanitarian relief operations is focused on developing inventory management policies for humanitarian warehouses (i.e., determining the size and frequency of orders, as well as the levels of safety stocks). Representative of the literature in this specific area are the papers by Beamon and Kotleba (2006a; 2006b). In their research, the authors discussed a project where an inventory management system for World Vision International warehouses was developed. They presented a humanitarian relief inventory model to determine optimal order quantities and re-order points for relief warehouses, and used simulation to compare the performance of the proposed mathematical model to both a heuristic and a naive inventory model. The authors showed how the mathematical model was able to minimize relevant inventory costs, achieve improved flexibility, and reduced response time.

Facility location research in the context of humanitarian relief is focused on determining the location of warehouses and distribution centers. Akkihal (2006), for example, developed a mixed-integer linear program to determine facility configurations where the objective is to minimize the average global distance from the nearest warehouse to the victims. Ultimately, the model is designed to determine the optimal locations for warehouses of non-consumable inventories required for the deployment of aid efforts. In the same line of research, Ukkusuri and Yushimito (2008) developed a facility location model for the prepositioning of supplies that takes into consideration the routing of vehicles as well as possible disruptions in the transportation network. Their model combines the most reliable path and an integer programming model to find the optimal location of supplies. Balcik and Beamon (2008) integrated facility location and inventory decisions for humanitarian relief in the context of quick-onset disasters. In particular, the authors developed a mixed-integer linear program that can be used to determine not only the number and location of distribution centers in a relief network but also the amount of relief supplies to be stocked at each distribution center in order to meet the needs of people affected by the disasters. The proposed model considers multiple item types, budgetary constraints and capacity restrictions. The authors developed scenarios for disaster locations and minimized the expected response time over all scenarios.

The literature related to the transportation and delivery of goods in humanitarian relief chains also presents a number of relevant applications. In this line of research, Haghani and Oh (1996) were the first to formulate the transportation of multiple commodities on a network as a multicommodity, multimodal network with the objective of minimizing the loss of lives. Barbarosoglu et al. (2002) developed a mixed integer mathematical programming model for helicopter mission planning during a disaster relief operation. In this framework, tactical decisions are made at the top level, while operational decisions are made at the base level. Consistency between the two models is achieved with an iterative coordination procedure.

MultiStage Stochastic Decision Modeling for Disaster Relief

In a dynamic situation such as the recovery from a disaster, multistage stochastic programming represents a technique that can be used to deal with the uncertainty that characterizes some of the parameters in a relief decision model.

Two-stage stochastic programming models have been one of the most widely used formulations. In these models, the decision maker is required to make a decision in the first stage, prior to knowing what value some random variable (typically, the demand for relief items) will assume. In the second stage, a recourse action is taken in order to compensate for the decision made in the first stage. The uncertain variables are usually modeled using a set of scenarios with associated probabilities of occurrence.

Since its inception by Dantzig (1955), several authors have studied different aspects of stochastic programming with recourse (Vladimirou and Zenios 1997; Haneveld and Vlerk 1999; Beraldi, Musmanno et al. 2000; Riis and Andersen 2005). The work by Birge and Louveaux (1997) discusses the most important concepts and applications.

Two-stage stochastic programming has been successfully applied to the study of different relief supply chain activities. In this line of research, Viswanath et al. (2002) focused on the transportation aspect of disaster relief. The authors developed a two-stage stochastic integer program with recourse for the disaster-related strategic problem of investing in the links of a stochastic network to improve its expected post-disaster performance. The proposed solution procedure is the optimization of the expected shortest path over the connected network realizations, subject to a bound on the probability of disconnected realizations. In the same line of research, Barbarosoglu and Arda (2004) developed a two-stage stochastic programming model to plan the transportation of vital first-aid commodities to disaster-affected areas during emergency response. The authors developed a multicommodity, multimodal network flow formulation that describes the flow of relief materials over a transportation network. In their model, randomness is represented by a finite sample of scenarios for capacity, supply and demand triplets. The model was tested using problem instances generated out of earthquake related data.

Tean (2006), focusing on disaster preparedness, combined transportation and facility location considerations in the development of a two-stage stochastic optimization model to assist in the pre-positioning of relief units and assets. The model takes into consideration different budget, transportation and physical limitations. As first-stage decisions, the author considered the expansion of infrastructure. The second-stage was represented as a transportation network problem with the goals of maximizing the number of survivors and the delivery of commodities. Stochastic data included the number of people affected in each potential area and the transportation times from each relief location. Heidtke (2007) extended the ideas presented by Tean and developed a two stage stochastic model to determine the optimal approach to reduce the so-called "gap of pain" (the temporal gap that develops between the exhaustion of state and local resources and the arrival of federal resources). The model also ensures the availability of critical supplies in the case of large-scale domestic disasters. In his research, the author characterizes the optimal solution as a combination of different pre-positioning and transportation strategies.

As discussed above, the existing literature has focused on different supply chain aspects such as inventory management, facility location, and transportation decision problems. Procurement in humanitarian relief logistics, however, has not been based upon scientific methodology. For this reason, the focus of this current research effort is aimed at developing a quantitative approach for procurement in humanitarian relief efforts.

Our work is most closely related to those authors that developed two-stage programs. Specifically, we intend to extend the existing body of knowledge and develop a model that will allow humanitarian relief logisticians to find the optimal quantities of relief items to order from the different available suppliers at each stage. A basic description of the procurement process in humanitarian relief chains is presented next.

Procurement in Humanitarian Supply Chains

The purpose of the procurement process in humanitarian supply chains is to ensure that humanitarian organizations have the supplies required to meet the needs for relief (PAHO 2001). Russell (2005) describes different features that help characterize the procurement process in humanitarian supply chains. The author explains that goods and services enter the relief supply chain through different sources, forms, and locations. Goods and services can enter the chain as in-kind donations (i.e., non-monetary goods and services) which may be solicited or unsolicited, or may be procured from suppliers. Goods commonly procured by humanitarian organizations include food items, water supply and sanitation equipment, shelter items, as well as medical equipment and drugs (Taupiac 2001).

In order to procure goods and services from suppliers, financial resources must be mobilized. Humanitarian organizations have multiple funding sources for each relief effort. They typically receive financial donations or grants, which come from a variety of sources. Donations and grants can be multilateral, administered by institutions that collect resources from sources in different countries and redistribute them, or bilateral, given directly from a donor institution to a recipient organization (Russell 2005).

Goods can be acquired in different ways such as in bulk or stored at the vendor until needed (Russell 2005). The procurement of goods can be done using local or global suppliers.

Local procurement, whenever possible, has the advantages of faster delivery times and lower transportation costs (PAHO 2001). Local procurement can also help in the recovery of the affected region by stimulating the local economy. However, local suppliers may not be able to provide the level of quality needed. In addition, local procurement can generate competition between organizations and result in shortages (PAHO 2001).

On the other hand, international procurement is done primarily to have access to larger quantities, lower prices and consistent quality. As long as delivery times and transportation costs are acceptable, procurement from global suppliers is a valid option for relief organizations. For example, international organizations such as the International Federation of Red Cross and Red Crescent Societies (IFRC) have agreements with global suppliers for items used consistently across disasters such as blankets, tents, tarps, and medical kits (Sowinski 2003). In most cases, humanitarian organizations will have multiple suppliers for each relief effort.

The Role of Information Technology

Humanitarian relief organizations have a common need for flexible information technology solutions that support procurement (Thomas and Kopczak 2005). As pointed out by the authors, the development of flexible technology-based solutions can help improve the responsiveness and the visibility of the materials pipeline.

Blecken and Hellingrath (2008) performed a review and assessment of supply chain management software tools available for humanitarian operations and identified those systems that included procurement modules. Procurement information may be stored in and retrieved from computerized disaster management software systems such as Sahana or the Humanitarian Logistics Software (HLS). HLS, for example, is a software system developed by the logistics department of the IFRC and the Fritz Institute which can be used to capture data and track information related to the procurement and distribution of goods to field units. Even though these software systems do not include any type of decision support functionality, they could be used as databases in order to support decision models such as the one presented in this paper.

The Humanitarian Relief Procurement Process

In responding to a disaster, relief organizations generally follow the basic process described below.

Immediately after a disaster occurs, relief organizations perform an initial assessment (usually within one day of the occurrence of the disaster) to estimate the supplies required to meet the relief needs of the affected population (Thomas 2003). At the same time, pre-positioned supplies available to the organization are also assessed in order to determine what supplies will need to be procured from suppliers. It should be noted that even though the pre-positioning of relief supplies increases the ability of humanitarian organizations to deliver aid faster, not all humanitarian organizations can afford to maintain a network of warehouses and distribution centers (Balcik and Beamon 2008). This fact illustrates the importance of developing a procurement decision model for humanitarian organizations.

Next in the process, logisticians translate the assessment into supply requirements. Demand for humanitarian relief supplies varies in terms of the magnitude, the criticality and the type of materials required. This demand is particularly hard to quantify due to the fact that it is caused by natural and man-made disasters and their magnitude, location and timing can be highly unpredictable. As pointed out by Thomas (2003), logisticians base their calculations on early rough estimates which can differ significantly in either direction as more accurate information is obtained.

Once all estimates have been developed, the humanitarian organization will try to procure the relief supplies from local suppliers and/or from centralized warehouses, should the required supplies be available in the organization's warehouses (Beamon and Balcik 2008). Those supplies that cannot be fulfilled by local suppliers or from centralized warehouses are procured from other global suppliers.

Appeals for donations are also made within one or two days of the onset of the disaster (Thomas 2003). Note that, as explained in the previous section, humanitarian organizations can receive both monetary and relief supplies donations.

As discussed above, logisticians' calculations can differ significantly in either direction as new information is obtained. In the case of the 2005 South Asia earthquake, for example, the IFRC preliminary estimate was to aid 30,000 families. As more information was received, the estimate was increased to 150,000 families (Davidson 2006). This example helps illustrate the point that it is difficult to quantify the impact of a disaster and that, as a result, humanitarian organizations will typically need to revise their initial estimates and decisions. A decision model for humanitarian relief procurement should, therefore, allow the decision maker to deal with parameters characterized by uncertainty (such as the demand for relief items) and provide a way to compensate for any bad effects that might be experienced as a result of making early response decisions based on limited information.

In this sense, a two stage stochastic program with recourse can prove useful. As discussed in previous sections, stochastic programming can allow a humanitarian organization to make a decision when some of the parameters are not known with certainty. In relief operations, humanitarian organizations must determine their procurement plans right after a disaster occurs, before the demand for relief is known with certainty (See Figure 5.2 below).

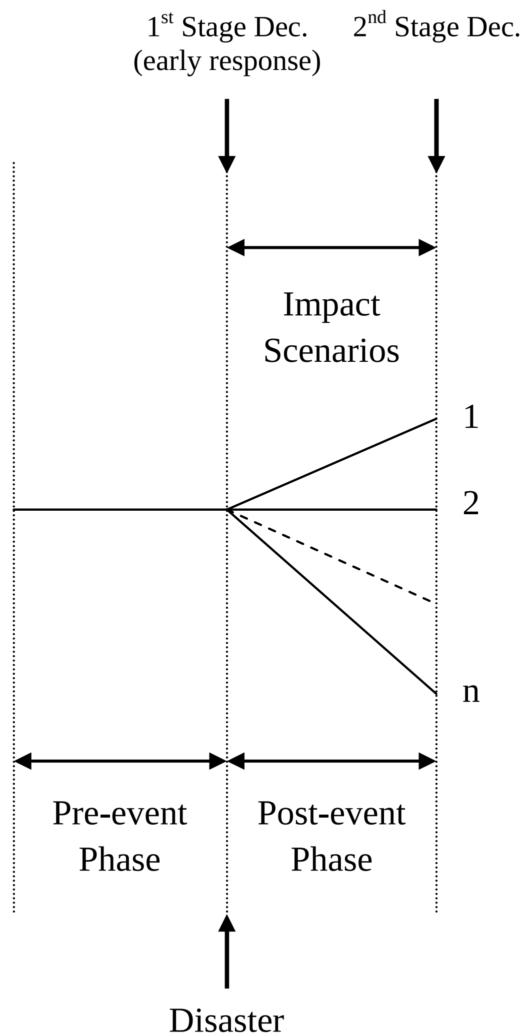

Figure 5.2: Representation of the two-stage procurement process in humanitarian relief

In our proposed decision approach, the initial rounds of procurement decisions are considered first-stage decisions, since they must be made before the random quantities are known. After the demand for relief and the available resources are known with certainty, humanitarian organizations can make changes to their procurement plans in order to compensate for discrepancies with the actual impact of the disaster. At this point, decision makers will determine how many additional items to order as well as how much demand for relief to leave unmet. These decisions are considered second-stage or recourse decisions.

Model

The goal of this research is to formulate a two-stage stochastic program with recourse that will allow humanitarian organizations to determine how much to order right after a disaster occurs, as well as what second-stage decisions they should make once more accurate information about the impact of the disaster is received. The uncertain parameters include the demand level for each relief item as well as the sizes of monetary and in-kind donations.

Data elements

The required data elements and the model formulation for the two stage stochastic humanitarian relief procurement model are presented next.

Decision Variables

x_{ij} = Quantity of relief item *i* to order from supplier *j* at stage 1

$y_{ij\omega}$ = Additional quantity of relief item *i* to order from supplier *j* at stage 2 under scenario ω

$z_{i\omega}$ = Integer decision variable that quantifies the unmet demand for relief item *i* under scenario ω

w_{ij} = 1 if supplier *j* is selected to deliver relief item *i*, 0 otherwise

Data Sets

I = The set of relief items

S = The set of available suppliers

Ω = Set of scenarios

Parameters

a_i = Quantity of item *i* available from warehouses (pre-positioned)

b = Available budget

c_{ij} = Unit purchase price from supplier *j* for item *i*

f_i = Penalty cost for each unit of unmet demand for item *i*

s_i = Number of suppliers to be selected for item *i*

$\overline{s_i}$ = Total number of available suppliers for item *i*

$\overline{u_{ij}}$ = Maximum capacity for item *i* available from supplier *j*

$\underline{u_{ij}}$ = Minimum order quantity for item *i* available from supplier *j*

$\overline{v_{ij}}$ = Maximum amount of business to be given to supplier *j* for item *i*

$\underline{v_{ij}}$ = Minimum amount of business to be given to supplier *j* for item *i*

Scenario-dependent data:

$d_{i\omega}$ = Demand for relief item *i* over the planning horizon under scenario ω

$k_{i\omega}$ = Quantity of in-kind relief item *i* donations under scenario ω

m_ω = Monetary donations under scenario ω

p_ω = Probability of scenario ω occurring

Model Formulation

$$\text{Min} \quad \left(\sum_j \sum_i c_{ij} x_{ij}\right) + \left(\sum_\omega p_\omega \left(\sum_j \sum_i c_{ij} y_{ij\omega} + \sum_i f_i z_{i\omega}\right)\right) \tag{1}$$

st

$$\left(\sum_j x_{ij} + a_i\right) + \left(\sum_j y_{ij\omega} + k_{i\omega} + z_{i\omega}\right) = d_{i\omega} \quad \forall i,\omega \tag{2}$$

$$\left(\sum_j \sum_i c_{ij} x_{ij}\right) + \left(\sum_j \sum_i c_{ij} y_{ij\omega}\right) \le b + m_\omega \quad \forall i,\omega \tag{3}$$

$$x_{ij} + y_{ij\omega} \le \min\left(\overline{v_{ij}}, \overline{u_{ij}}\right) w_{ij} \quad \forall i,j,\omega \tag{4}$$

$$x_{ij} + y_{ijw} \ge \max\left(\underline{v_{ij}}, \underline{u_{ij}}\right) w_{ij} \quad \forall i,j,\omega \tag{5}$$

$$\sum_j w_{ij} \le s_i \quad \forall i \tag{6}$$

$$x_{ij} \ge 0 \quad \forall i,j \tag{7}$$

$$y_{ij\omega} \ge 0 \quad \forall i,j,\omega \tag{8}$$

$$z_{i\omega} \ge 0 \quad \forall i,\omega \tag{9}$$

$$w_{ij} \in \{0,1\} \quad \forall i,j \tag{10}$$

The objective function, (1), minimizes procurement and shortage costs across all possible scenarios. Our objective function has two distinct components: total relief shortage costs, denoted by

$$\sum_\omega p_\omega \left(\sum_i f_i z_{i\omega}\right) \tag{11}$$

and total procurement costs, denoted by

$$\sum_j \sum_i c_{ij} x_{ij} + \sum_\omega p_\omega \left(\sum_j \sum_i c_{ij} y_{ij\omega} \right) \tag{12}$$

Procurement costs are represented by the sum of first-stage procurement costs plus the expected second-stage procurement costs. To compute total procurement costs, we use the same first-stage decisions about how many items to order as we would in the case of a single-stage deterministic model. However, in our model we also need to determine second stage order quantities for each possible impact scenario. For this purpose, the objective functions weigh each of the second-stage costs by their associated probability of occurring. The expected second stage procurement costs are then added to the first-stage costs to determine the total procurement costs.

Constraint set (2) tries to ensure that the quantity procured for each relief item is appropriate in order to satisfy the quantity demanded during the planning horizon. Quantities of relief items available include prepositioned items, items procured from suppliers, and items in the form of in-kind donations. The right hand side of constraint set (2) represents the set of possible demand scenarios. Constraint (3) makes certain that total procurement costs do not exceed the level of funds available (which include both budgeted funds as well as monetary donations).

Constraint set (4) ensures that a supplier’s capacity for an item, or the extent of the desire of the organization to procure from that supplier, is not exceeded. For example, a humanitarian organization may want to limit the amount of business from a particular supplier in order to balance the mix between international and local suppliers. Alternatively, an organization might be interested in reducing its dependence on a particular supplier and, thus, increase its supply chain resilience to supply disruptions.

Constraint set (5), on the other hand, enforces the size of any minimum order quantities that might be determined by the supplier or by the organization. As discussed in previous sections, humanitarian organizations may have already signed agreements with suppliers for items used consistently across disasters. Constraint (6) establishes the maximum number of suppliers from which the organization would be interested in procuring a certain item.

Finally, constraint sets (7) and (8) ensure that order sizes be non-negative, while constraint sets (9) and (10) enforce additional binary and non-negativity conditions.

Application Example

To support the usefulness of the proposed model as a decision-making tool for humanitarian relief organizations, we evaluate the performance of the model using a set of randomly generated impact scenarios. In our example, the humanitarian organization must determine its procurement plan right after a sudden onset disaster occurs (e.g., an earthquake), before knowing with certainty what the level of donations and the demand for relief will look like. After the uncertain parameters are realized, the humanitarian organization must decide how many additional items to order and how much relief to leave unmet.

In the application example, we consider three possible levels of demand for relief (low, medium and high) and three possible donation levels (low, medium and high) for a total of nine possible scenarios (See Figure 5.3). As shown in the figure below, the best possible scenario is characterized by a low level of demand for relief and a high level of donations, while the worst case scenario is characterized by a high demand for relief and a low level of donations.

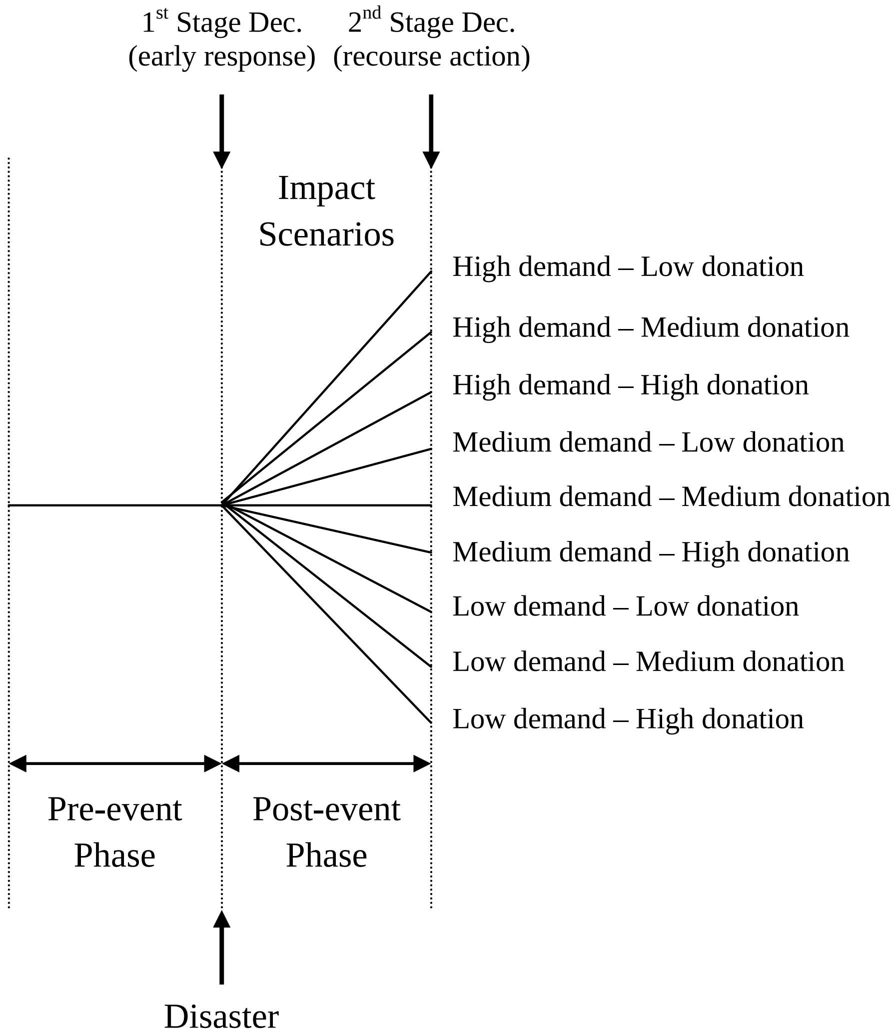

Figure 5.3: Representation of possible scenarios for the two-stage humanitarian relief procurement model

We consider five relief items that can be procured from ten candidate suppliers. We should note that, typically, relief commodities are delivered in the form of standard modules such as hygiene kits (Balcik and Beamon 2008). For this reason, the number of different commodities that must be selected in relief operations does not tend to be considerable. Table 5.1 below displays the parameter values that were used in the test case.

Scenario	Demand (beneficiaries)	Donations ($)
1	30,000	300,000
2	30,000	200,000
3	30,000	50,000
4	20,000	300,000
5	20,000	200,000
6	20,000	50,000
7	10,000	300,000
8	10,000	200,000
9	10,000	50,000

Initial Budget	$200,000
Penalty cost for unmet demand	$20/unit

Table 5.1: Parameter values used in the test case

Unit purchase prices ranged between $3 and $7, while penalty costs per unit of unmet demand were set at $20. It is particularly important to set a big enough penalty cost for unmet demands because, otherwise, the model could conceivable minimize total overall costs by choosing to not fulfill relief demand, even though resources might be available.

We first solve the humanitarian procurement problem using the stochastic formulation. In order to validate the results of the proposed model and place them into context, we then re-solve the problem using two additional solution approaches. These two approaches are briefly described next.

Wait-and-See Solution Approach

In this alternate approach to solving the procurement problem, we assume that perfect information about future realizations of the uncertain parameters is readily available. As a consequence, each individual scenario can be optimized independently. The Wait-and-see solution represents the expected value of the solution over this set of scenarios. We then use this solution along with the original two-stage Stochastic solution in order to determine the Expected Value of Perfect Information (EVPI). In the case of a minimization problem, EVPI is computed as:

$$EVPI = \text{Stochastic solution - Wait-and-see solution} \tag{13}$$

EVPI can be interpreted as the maximum amount of money a decision maker should be willing to pay for perfect information about the future. In our context, humanitarian organizations could use this information to determine how much to invest in better forecasts.

Expected Value Solution

In the next heuristic solution approach, the humanitarian organization bases its procurement plan on the average (expected) value of the uncertain parameters, rather than planning for each possible scenario. This type of solution approach is called the Expected Value Solution. We calculate the expected demand for relief and the expected level of donations and then determine the optimal procurement plan based on those estimates (i.e., we replace our uncertain parameters by their expected values). We use the Expected Value solution along with the Stochastic solution in order to determine the Value of the Stochastic Solution (VSS). In the case of a minimization problem, VSS is computed as:

$$VSS = \text{Expected Value solution - Stochastic solution} \tag{14}$$

VSS measures the potential benefit from solving a stochastic program over solving a deterministic program where expected values are used to replace random parameters (Birge 1982). In our particular context, humanitarian organizations could use this information to determine whether it is worth the extra effort to create a stochastic model and all the corresponding possible scenarios, as opposed to using the less sophisticated expected value model.

Results

We now present computational results from our randomly generated instances. The software used to solve the model was the Risk Solver Platform from Frontline Systems, Inc. (www.solver.com). Table 5.2 below displays the results of the stochastic approach.

	Scenario		**Relief Shortages**	**Procurement Costs**
	Demand	**Donations**	**(%)**	**($)**
1	High	High	16.69	483,228
2	High	Medium	26.84	392,295
3	High	Low	29.59	231,136
4	Medium	High	10.68	412,544
5	Medium	Medium	14.85	363,674
6	Medium	Low	23.96	222,363
7	Low	High	5.96	332,369
8	Low	Medium	8.90	273,038
9	Low	Low	11.80	213,435

Table 5.2: Stochastic model results

In the example results above, we can identify a series of patterns that illustrate how the stochastic model is able to capture the interrelationships between the uncertain parameters. It can be observed that as the level of donations increases, the level of relief shortages is reduced. On the other hand, as the severity of the disaster increases, the level of shortages increases, other things held equal.

With respect to procurement costs, the patterns are not as clear. However, it can be observed that procurement activities increase as the level of donations is increased which, in turn, results in reduced relief shortages. The reason that helps explain this pattern is the following: as a humanitarian organization receives donations, more funds are available to procure items; at the same time, if demand increases, the organization will then try to procure more items to satisfy the increased demand for relief.

Next, in order to validate our stochastic model results, we compare the wait-and-see solution to the stochastic programming solution, and we also compare the expected value solution to the stochastic programming solution. A summary of the results for the different solution approaches is presented in Table 5.3.

Stochastic	**Wait-and-see**	**Expected Value**	**EVPI**	**VSS**
\$331,774	\$301,516	\$354,590	\$30,258	\$22,816

Table 5.3: Summary of results

The wait-and-see approach yields a solution that is 9.12% better than the stochastic model solution (as measured by the EVPI). We should note that the wait-and-see solution represents an upper bound or limit for the stochastic model as this approach assumes we know for certain which scenario will occur. Thus, from an implementation point of view, the wait-and-see solution has no practical value. Nonetheless, the EVPI and the wait-and-see solution do provide some useful insights. The decision maker can use this information to determine how much more efficiently the organization could use its resources should more accurate information to plan for a specific relief scenario was available. That information could then be used to decide, for example, whether the organization should invest in better forecasting methods, or whether the organization should collaborate and share information with other organizations to develop better forecasts.

On the other hand, the stochastic model yields a solution that is 7% better than the expected value solution (as measured by the VSS). Unlike the wait-and-see approach, the expected value approach does provide a solution that represents an implementable procurement plan. However, the expected value solution is based on hypothetical average scenarios, and fails to consider all the complex inter-relationships among all the other possible scenarios. This limitation is reflected in the VSS and allows us to make the claim that the solutions obtained with the stochastic model represent the best implementable solution. Overall, the difference between the stochastic model solution and the expected value solution helps illustrate the point that it is worth the extra effort to create a stochastic model, as opposed to using the simpler expected value model.

Conclusions

This paper represents the first step in developing procurement decision models for humanitarian relief.

We have formulated and solved a two-stage, linear, mixed-integer procurement optimization model to provide guidance in relief operations. The model takes into account different relief uncertainties (such as the level of donations), different logistics constraints (e.g., the capacity of suppliers) and other operational constraints in order to minimize expected demand shortages as well as total procurement costs.

A sudden onset disaster test case was developed and tested. The example presented in previous sections showed how decision makers might need to carry out significant modifications to the original actions during the recourse stage. The example also illustrated how our decision modeling tool can allow decision makers to better structure the procurement of relief items and avoid wasted time and effort to save human lives and alleviate suffering.

We believe lessons from humanitarian logistics can be important for commercial supply chains. For example, disaster relief supply chain management can show how to manage uncertain environments and how to react to unpredictable disruptions. As commercial supply chains become increasingly agile, the ideas from the field of humanitarian relief supply chain management will prove relevant to the commercial sector.

Our work thus provides researchers in supply chain management with a new application of mathematical programming and allows them to compare and contrast procurement decisions in humanitarian relief supply chains and commercial supply chains. Future work may look at formulating a combined procurement and transportation model. As discussed in previous sections, the humanitarian logistics literature presents a number of relevant applications related to the transportation and delivery of goods in humanitarian relief chains (Haghani and Oh 1996; Barbarosoglu, Ozdamar et al. 2002; Barbarosoglu and Arda 2004). The development of a combined procurement and transportation model would further strengthen the importance of this work in the context of providing computer-aided decision support for humanitarian logistics.

Limitations and Directions for Future Research

As mentioned above, this paper represents the first step in developing procurement decision models for humanitarian relief. We now discuss some of the limitations of our model and identify a series of relevant future research directions.

The focus of this paper was the procurement of relief supplies. Future research could focus on the procurement of services, which represent a significant portion of procurement expenditures. Taupiac (2001), for example, estimates that the procurement of services accounts for approximately 40% of all expenditures.

Our model formulation assumed there were no item losses in the relief effort. However, in some humanitarian relief situations, decision makers must also estimate how much material may be lost before it gets to the recipients (due to corruption, etc.) and make decisions accordingly. For example, in the Somalia famine crisis there were severe losses before any relief food could get through to the beneficiaries because a large proportion of the relief food had to be used as bribes to local warlords (Long and Wood 1995). For those situations where having supplies lost or stolen cannot be prevented, out model could be extended by incorporating an additional uncertain parameter to develop a set of scenarios with different potential losses of procured items.

Another limitation of the proposed model is that the model does not differentiate between local and international suppliers. A potential path for future research includes analyzing alternative procurement plans with different mixes of local and international suppliers. In this sense, some of the topics that could be studied include the impact and stimulation of the local economy along with issues related to delivery speed and product quality.

Our two stage application focused on sudden onset/impact disasters (e.g., earthquakes, tsunamis or landslides). With additional development and testing, the model could also be applied to a wide range of natural and man-made disasters. In the case of gradual onset disasters, such as floods, our model could be extended by incorporating an additional stage that would represent short-term prepositioning decisions (See Figure 5.4 below). The decision maker could, thus, evaluate the effect of combined relief item procurement and pre-positioning plans. Future work could also include adapting our decision model to represent procurement activities in projects aimed at long term social and economic development.

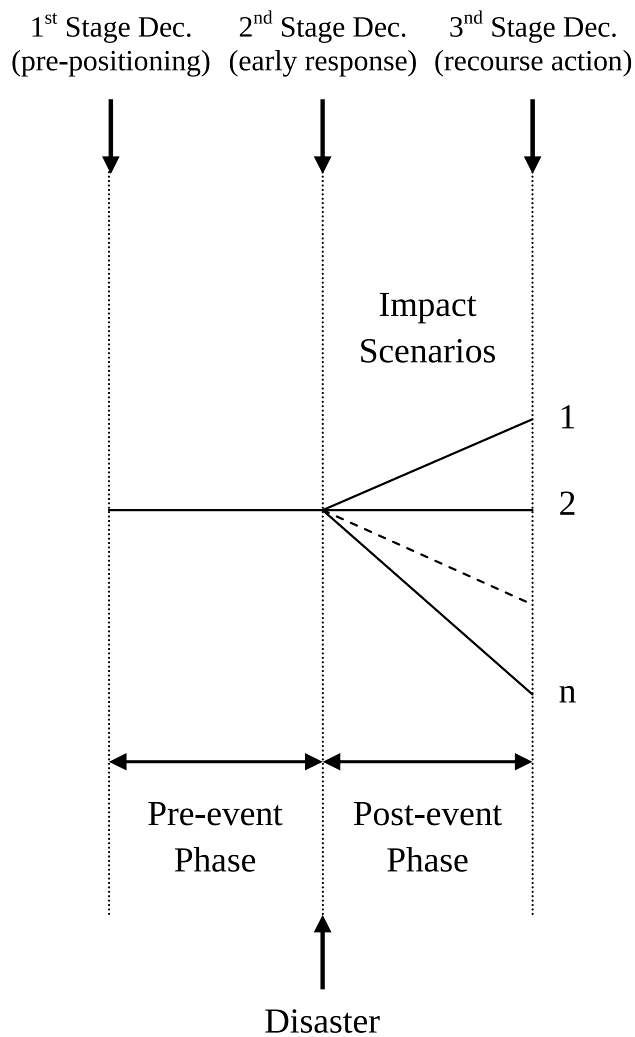

Figure 5.4: Representation of a three-stage model for gradual onset disasters

Finally, our model assumes that supplier prices stay constant regardless of the size of the order. In this sense, future research should also address other problems such as order size discounts and bundle bidding. Those two issues represent valid examples of the available cross learning opportunities between the business and the humanitarian logistics sectors.

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CHAPTER 6

SUMMARY AND CONCLUSIONS

Chapter 6

Summary and Conclusions

Summary

The overall purpose of this dissertation was to develop a series of quantitative decision models to help address some of the challenges faced by humanitarian logistics. Specifically, the present work was aimed at developing a multicriteria scheduling model to support the assignment of volunteers in long term development humanitarian aid, a multicriteria scheduling model to support the management of volunteers in humanitarian relief efforts that combined fuzzy logic and efficiency analysis notions in order to better represent the decision maker's knowledge and preferences, and a two-stage stochastic model to improve the procurement of goods in humanitarian relief efforts.

Conclusions

The first study discussed the development of a spreadsheet-based multicriteria scheduling model for a small development aid organization in a South American developing country. The study exemplified how the development of small, focused applications of traditional OR/MS topics can help in this type of environment by supporting and promoting more effective and efficient decision making. Since these types of organizations rely heavily on the use of volunteers to carry out their social mission, it is particularly important that they manage their volunteer workforce efficiently. Our work demonstrated not only how the proposed model helped to reduce the number of unfilled shifts and to decrease total scheduling costs, but also how it helped to better satisfy the volunteers' scheduling preferences, thus supporting long-term retention and effectiveness of the workforce.

The purpose of the second study was to develop a decision model to assist in the management of humanitarian relief volunteers. Our research identified a series of volunteer management challenges faced by humanitarian organizations and explained how volunteer labor force models differed from traditional business models. We also showed how our optimization model incorporates the multicriteria nature of volunteer management and how our model can support the assignment of both individual volunteers and volunteer groups to tasks. In addition, we analyzed two complementary solution methodologies to incorporate the decision maker's preferences and knowledge and allow him/her to consider conflicting objectives. In the first place, we showed how our model can be used to consider the impact of tradeoffs between two conflicting objectives in humanitarian relief scenarios. Our research also found that the fuzzy multiple objective solution approach provides solutions that are as good as the solutions obtained using the efficient frontier method, and recommended its use as a guidance tool to further support the decision making process.

The third study discussed the development of a decision model for the procurement of goods in humanitarian efforts, a topic that had only been discussed in a qualitative manner in the literature. In our research, we characterized humanitarian procurement processes in the context of relief efforts, and explained how our proposed approach could help address the need for adjusting the decision-making process under conditions of extreme uncertainty. In this sense, our work showed how decision makers might need to carry out significant modifications to their original decisions, and illustrated how our decision modeling tool can allow them to better structure the procurement of relief items and avoid wasted time and effort to save human lives and alleviate suffering.

Our work thus introduced three new decision models for humanitarian logistics problems. Throughout the thesis, we showed how the models developed can be utilized by decision makers in the field of humanitarian logistics to make scheduling and procurement decisions more efficiently and effectively. The models developed in this thesis also provide researchers in supply chain and operations management with new applications to compare decision making in humanitarian and business contexts.

Future research

This work has led to a number of conclusions discussed above. There also exists potential to study other relevant aspects of the field of humanitarian logistics. All of the following extensions would be valuable contributions to the work already completed in this thesis.

Volunteer Management Extensions

- **Combined planning and scheduling model:** Future research could look at formulating a combined planning and scheduling model. A workforce planning model could be used to determine the volunteer workforce levels required by a humanitarian organization (i.e., how many volunteers should be recruited), and then this information could be fed into the scheduling model.
- **Group dissatisfaction factor:** As discussed in Chapter 4, including a dissatisfaction factor in our volunteer management model would allow the decision maker to analyze alternative scheduling decisions with different mixes of individual volunteers and

volunteer groups, to prioritize the scheduling of volunteer groups, and to quantify the relative importance of satisfying volunteer groups of different sizes.

- **Alternative humanitarian applications:** Our volunteer management model formulation could be applied to other humanitarian contexts. Future research could look at ways of adapting the basic model formulation to meet other humanitarian scenarios (e.g., Habitat for Humanity).
- **Additional objectives:** An example in Chapter Four showed how a third objective representing total schedule costs could be added to the fuzzy model formulation. Future research may examine the use of the fuzzy multiple objective approach to include additional objectives as required by a humanitarian organization.

Humanitarian Procurement Extensions

- **Procurement in long term development aid:** Since the focus of this thesis was limited to procurement in humanitarian relief efforts, future research could look at adapting the decision model developed in Chapter 5 to represent procurement activities in projects aimed at long term social and economic development. In this sense, future work could combine the solution methodology presented in Chapter Four with a single stage deterministic version of the procurement model developed in Chapter Five. Extending our relief model to aid contexts would be similar to the volunteer management work presented in Chapters Four (which focused on humanitarian relief) and Three (which focused on long term development aid).

- **Procurement of services in humanitarian relief chains:** We mentioned in Chapter Five that the procurement of services in humanitarian relief efforts accounts for a significant portion of all procurement expenditures. Future research could look at the business literature in order to develop a procurement model for services in the humanitarian sector, which include, for example, transportation, inspection and consulting services.
- **Combined procurement and transportation model:** Future research could look at formulating a combined humanitarian procurement and transportation model. Such extension would allow humanitarian organizations to determine both the best procurement plan and the best way to deliver the relief items.
- **Item losses:** As explained in Chapter Five, humanitarian organizations need to estimate in some relief situations how much material will be lost before it gets to the recipients. For those specific situations, out model could be extended by incorporating an additional parameter to represent potential losses of procured items.
- **Local versus international suppliers:** An interesting future research direction includes adapting out model to analyze alternative procurement plans with different mixes of local and international suppliers. This would allow us to study issues such as the different impact of those plans on the local economy, on delivery speed and on overall product quality.
- **Three-stage humanitarian procurement model:** Chapter five provided an example of a three-stage procurement model. Such extension would allow us to combine relief item procurement and pre-positioning decisions and to study a wider range of gradual onset disasters.

Additional Modeling Extensions

- **Spreadsheet modeling:** Based on the lessons learned from Chapter Three, future work could focus on developing a spreadsheet based graphical user interface for the models developed in Chapters Four and Five in order to make the input of data and the display of results more user-friendly. In this way, the models developed in those two chapters could be used by decision makers in humanitarian organizations who might not be familiar with mathematical programming techniques.
- **Membership function shapes:** We noted on Chapter Four that our model was limited to the use of linear membership functions for the sake of efficiency with respect to computability. From a modeling perspective, an analysis of the effects of nonlinear and discrete shaped membership functions on the mapping of solutions would be an interesting future research direction.
- **Alternative application areas:** Even though our research in Chapter Four combined efficiency analysis and fuzzy logic to solve volunteer labor scheduling problems, it has broader implications not only for other types of scheduling problems commonly found in service applications but also for all other types of multiple criteria decision making problems. As discussed above, this solution methodology could be extended to model conflicting objectives in humanitarian procurement decision models

Overall, the models developed provide decision makers in the field of humanitarian logistics with new approaches for making scheduling and procurement decisions more efficiently and effectively in their respective roles. Continued work along these paths will help the humanitarian logistics field continue to gain popularity and evolve with respect to the use of decision tools and technologies.

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